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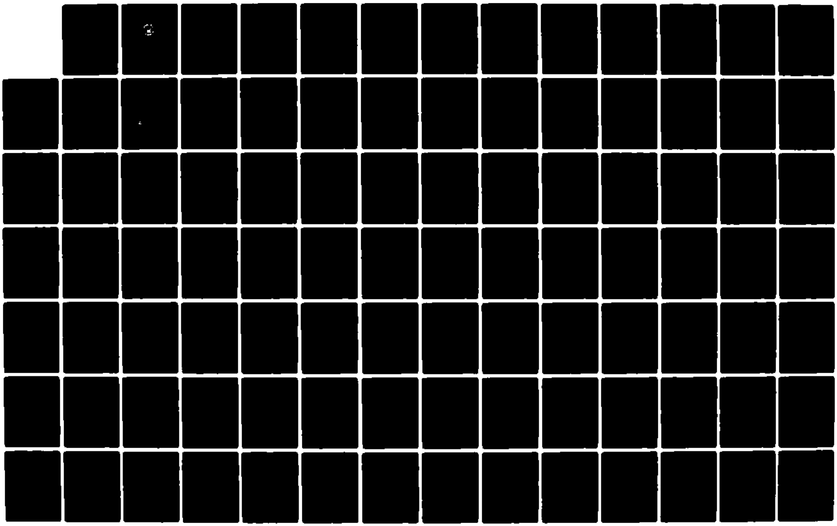

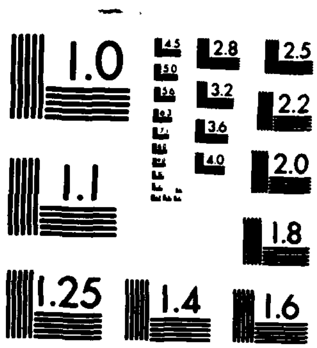

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THESIS

AN ANALYSIS OF MODELS FOR FORECASTING
REPAIRABLE CARCASS RETURNS

by

Douglas Martin Hartman

October 1982

Thesis Advisor: F. R. Richards

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An Analysis of Models for Forecasting Repairable Carcass Returns

by

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

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October 1982

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This thesis evaluates techniques for forecasting the return of failed repairable spare parts (known as carcasses) within the U. S. Navy supply system by comparing the model currently implemented in the Uniform Automated Data Processing System Inventory Control Point (UICP) program with several alternative forecasting models to determine if an improvement can be achieved in forecasting effectiveness. The current model uses an exponential smoothing procedure and applies several filtering processes to determine the appropriate smoothing constant value. The alternative models employ forecasting techniques such as moving average, moving least squares, adaptive response rate, and regression analysis. Each model is then synthesized with actual U. S. Navy supply system data and its performance measured by a set of evaluation criteria. The results indicate that the current UICP forecasting model cannot be improved substantially and that a filtering process is critical to the performance of any model applied to real world data.

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I. INTRODUCTION

This thesis compares the model currently implemented in the Uniform Automated Data Processing System Inventory Control Point (UICP) program for forecasting the return of failed repairable spare parts (known as carcasses) with several alternative forecasting models to determine if an improvement can be achieved in forecasting effectiveness. While the results of a study of forecasting techniques could apply to many aspects of the U.S. Navy repairable system, this study will specifically address only SPCC-managed non-aviation items.

The primary function of the repairables inventory system is to maintain a high state of fleet readiness through material availability by efficient workload scheduling and maximizing financial resource allocations. The motivation behind this study is to look at one portion of the logistics system and determine if the currently employed forecasting techniques could be improved towards this end.

The forecasting of carcass returns within the supply system plays a key role in both workload planning and budgeting. The carcass return forecast and the estimated demand determine the funding levels required to service the failed units for reissue and the shortfall of units that must be funded as new purchases. Currently SPCC uses an exponential smoothing model with filters to forecast carcass returns. The scope of this thesis will be to formulate and test various forecasting models and to compare them to the current SPCC model. These models employ forecasting techniques such as moving average, moving least squares, adaptive response rate, and several regression analysis schemes. Each mode will be analyzed using two years of actual demand and carcass return data from a selected subgroup of repairable items managed by SPCC and evaluated with respect to various decision criteria.

The thesis will first provide an overview of the repairable systems within the U.S. Navy and present the role of the Inventory Control Point (ICP) in the system. The overview includes discussion of the data files and the programs and basic inventory models used by the ICP. Then the forecasting algorithms and the motivation behind each examined forecasting model is presented. A separate section on model building concentrates on the evolution of regression models. The data selection criteria and the data collection procedure are addressed, and the measures of effectiveness that are used to evaluate the models are discussed. Finally, the numerical results of the study are presented and discussed with respect to applicability and implementation. In general, the results indicate, first, that the current UICP forecasting model cannot be substantially improved using the types of models considered here and, second, that a filtering process is critical to the performance of the models when applied to real-world data.

II. THE CURRENT NAVY REPAIRABLES SYSTEM

A. THE REPAIRABLES CYCLE

Repairable spare parts are big business in the Navy today. Repairables became an economic necessity with the advent of increasing technological complexity of weapon systems and the rising costs of their components. Many of those components are not repairable onboard ship or at intermediate maintenance levels and must be repaired at a depot (Depot Level Repairables - DLR). Repairable items include electron tubes, circuit boards, test equipment, pumps, motors, turbine rotors, amplifiers, power supplies, etc. A key to fleet readiness is the availability of spare components within the supply system to keep these systems operational. Today, SPCC manages approximately 100,000 repairable items accounting for annual sales of approximately $20 million.

A part is classified as a repairable item rather than a consumable item if it is more economical to take that part back into the supply system and repair it for future use rather than purchase a new one. Repair costs including transportation, storage and handling generally average 40-60 percent of the replacement price of the item. Repair turnaround time versus procurement lead time is also a key factor with repair times normally ranging from 90 to

180 days, as compared to the purchasing cycles of up to two years. The reasons for this difference in leadtimes vary, but, in general, the "repair bench" and piece parts are in place or readily accessible, whereas the manufacturer must tool up and obtain the raw materials and components to produce a new part. In other cases, there may be no procurement sources available and repair is the only alternative.

The addition of a repairable system within the supply distribution system adds a unique dimension from the logistics point of view. In the private sector the logistician's work is basically completed once the product reaches the customer. If the product subsequently fails, the customer is responsible for pursuing repair actions or replacement. However, parallel systems, one for forward physical distribution and one for failed unit (carcass) returns or retrogrades, must be formed to support Navy repairables. Carcass collection and overhaul points must be designated, transportation facilities established, and complex inventory control decisions must be made. These decisions include the number of carcasses to induct into the repair cycle and when, the number of new DLRs to procure to replace normal attrition and increased demand, and the number of units to procure based upon manufacturing costs and lead times and the reorder levels.

The Navy repairable system for an SPCC managed item is depicted graphically in Figure 1. Figure 1 illustrates the theoretical flow of the DLR and attendant information flow. When a failure occurs, the customer initiates a requisition or "demand" document to obtain a replacement part (designated Ready For Issue (RFI)). Under the Area Supply Support Concept, the customer submits his requisition to the nearest stock point. This allows the stock point to record a demand, or hit, for future stocking computations.

If the stock point has the item in stock, it issues the part to the customer and electronically transmits a report of the issue to the ICP via the Transaction Item Reporting (TIR) system. The TIR is processed by the ICP, adjusting on-hand balances for that part, recording the demand and establishing a "due-in" for the NRFI (Not Ready For Issue) unit.

If the stock point is temporarily out of the desired item or does not normally carry the part, the requisition is forwarded to the ICP for disposition. The ICP processes the demand by forwarding it to an activity that does have stock on-hand or backorders the items for release against forthcoming RFI assets, and adjusts the records accordingly.

When the customer receives the RFI unit and installs it, he is operational again. His role in the cycle is not

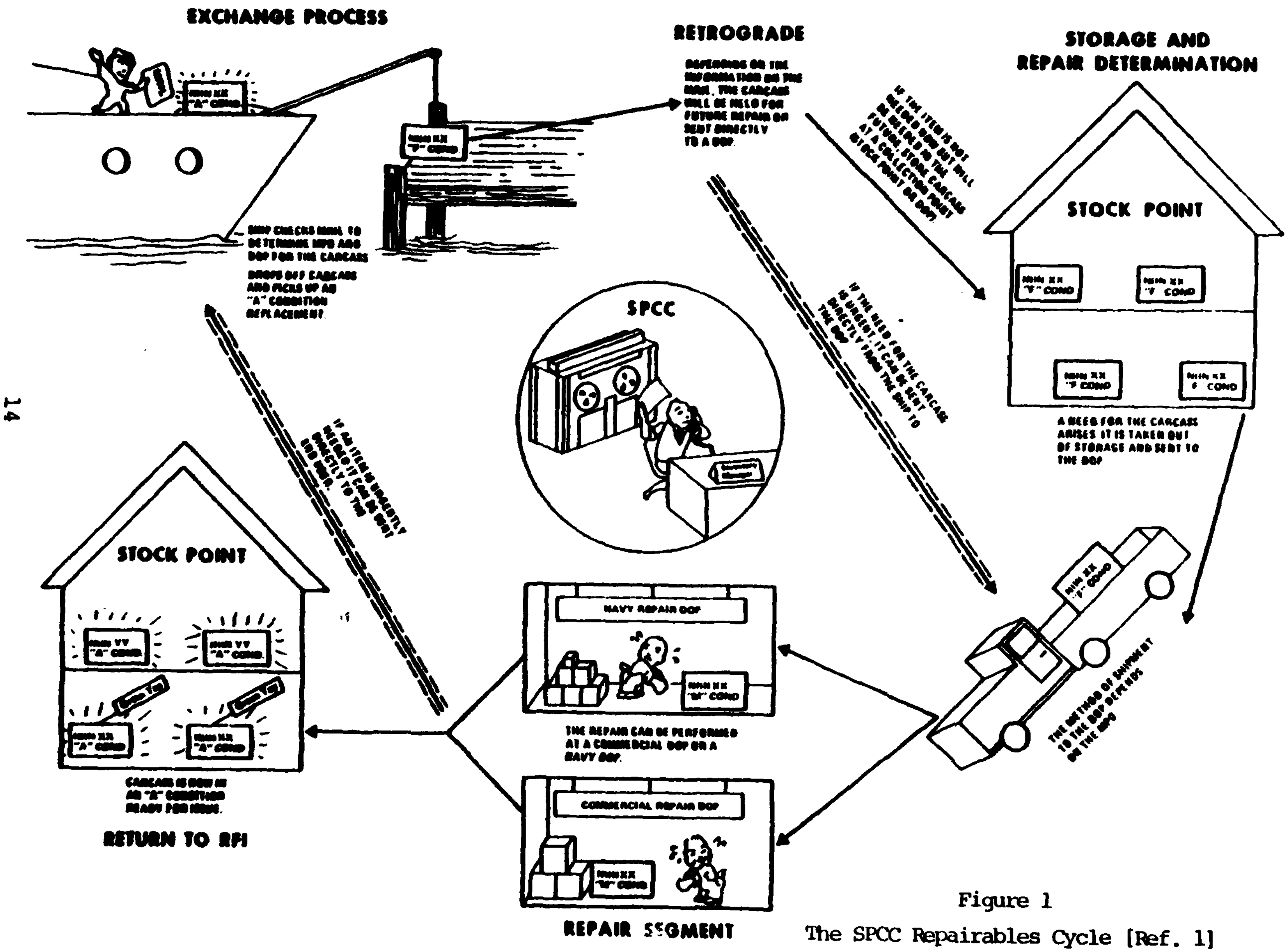

Figure 1

The SPCC Repairables Cycle [Ref. 1]

complete, however, until he returns the failed unit (called a carcass and designated NRFI) to the system so it can be repaired and placed back on the shelf as an RFI unit. The customer consults the Master Repairable Item List (MRIL) to determine the disposition of the carcass. The MRIL includes the Movement Priority Designator (MPD) which is assigned by the ICP and determines the transportation priority of the movement of the carcass. Once the NRFI unit is turned in (either at the time the initial demand is placed or subsequent to that), the stock point notifies the ICP through a TIR and the due-in is cancelled. The collection point (CP) is a location designated to receive and store all NRFI units until they are to be inducted into the repair cycle. It can be either a stock point or the designated overhaul point (DOP). Therefore, if the stock point receiving the NRFI item is the CP, it holds the material; otherwise it forwards the unit to the designated CP in accordance with MPD. The inventory manager then decides how best to get a unit back on the shelf at the issuing stock point. This decision may mean the initiation of a repair action on a failed unit or the procurement of a new RFI item. These decisions are a function of recurring demand forecasts, carcasses currently in the repair cycle, NRFI assets awaiting repair at the CP, repair lead times, procurement lead times, and budgetary constraints. If the decision is to repair the unit, the unit is inducted into the repair cycle at one of over 20 Navy industrial facilities or 250 commercial designated overhaul points. Once repair action is complete, the RFI item is directed to a specific stock point by the ICP in the Redistribution Phase. The stock point receives and stores the RFI item until it is subsequently required to fill a requisition. If the decision to procure a new unit is made, a contract is established with a manufacturer and the new unit is sent to the designated stock point.

Figure 2 illustrates the repairables pipeline. Ideally, the system should function as closed loop with no loss of units from turn-in to reissue. In practice, losses of units occur at three points: (1) during the Exchange Phase when the customer either does not have an NRFI unit to turn in or it is lost in transit to the collection point; (2) during the Retrograde Phase when units are misplaced or are determined irreparable by the stock point and surveyed; and (3) during the Repair Phase when the unit is determined to be beyond economic repair by the DOP. These losses or "attrition" demands must be made up by an infusion of units into the system through procurement.

This general outline applies only to existing systems and does not address non-recurring demands such as initial outfitting, planned maintenance, ROH refitting/backfitting,

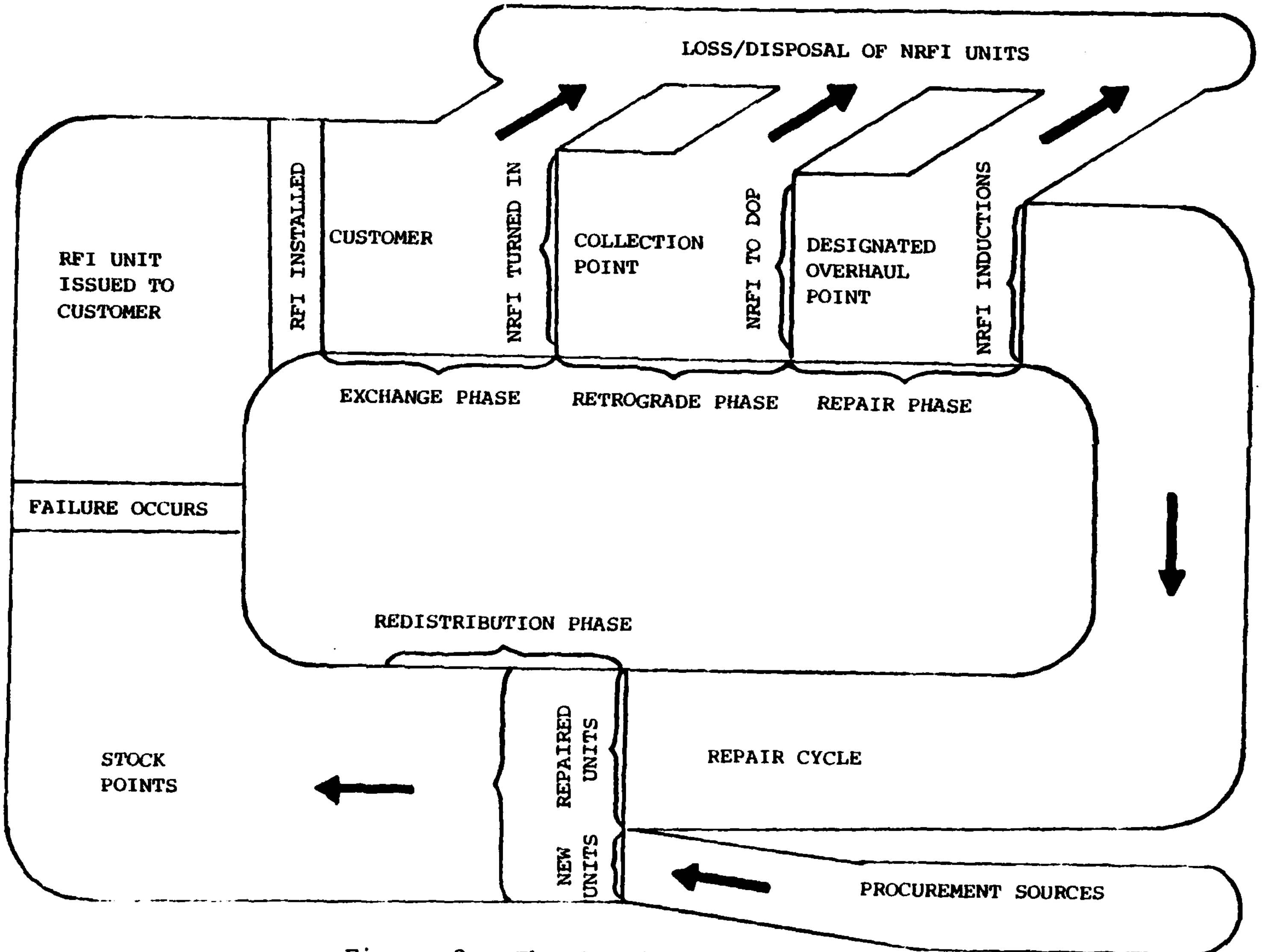

Figure 2. The Repairables Pipeline.

etc., which are funded by the Hardware Systems Command (HSC) (e.g. NAVAIR, NAVSEA, NAVELEX, etc.). The recurring demand portion of the repairables system becomes involved only after the first failure for these items.

B. THE ICP AND THE UICP SYSTEM

To get a basic understanding of the role that carcass return forecasting plays in the overall repairables cycle it is important to look at the ICP functions. The previous general discussion of the repairables cycle can be represented basically as a wheel of repairables activity through the Uniform Automated Data Processing System - Inventory Control Point (UICP) generated and maintained by the Fleet Material Support Office (FMSO). Item managers, located at each ICP, are personally responsible for monitoring and directing the inventory control life of specific items. The item manager is the human aspect of the UICP system. He receives the UICP-generated information and makes critical inventory control decisions concerning the procurement, repair, and distribution of an item. The following presentation will discuss some of the UICP files that are maintained in support of the repairables program and associated UICP programs that actually manipulate the files to provide the repair/procure decisions and determine budgetary requirements for the system. Figure 3 is a

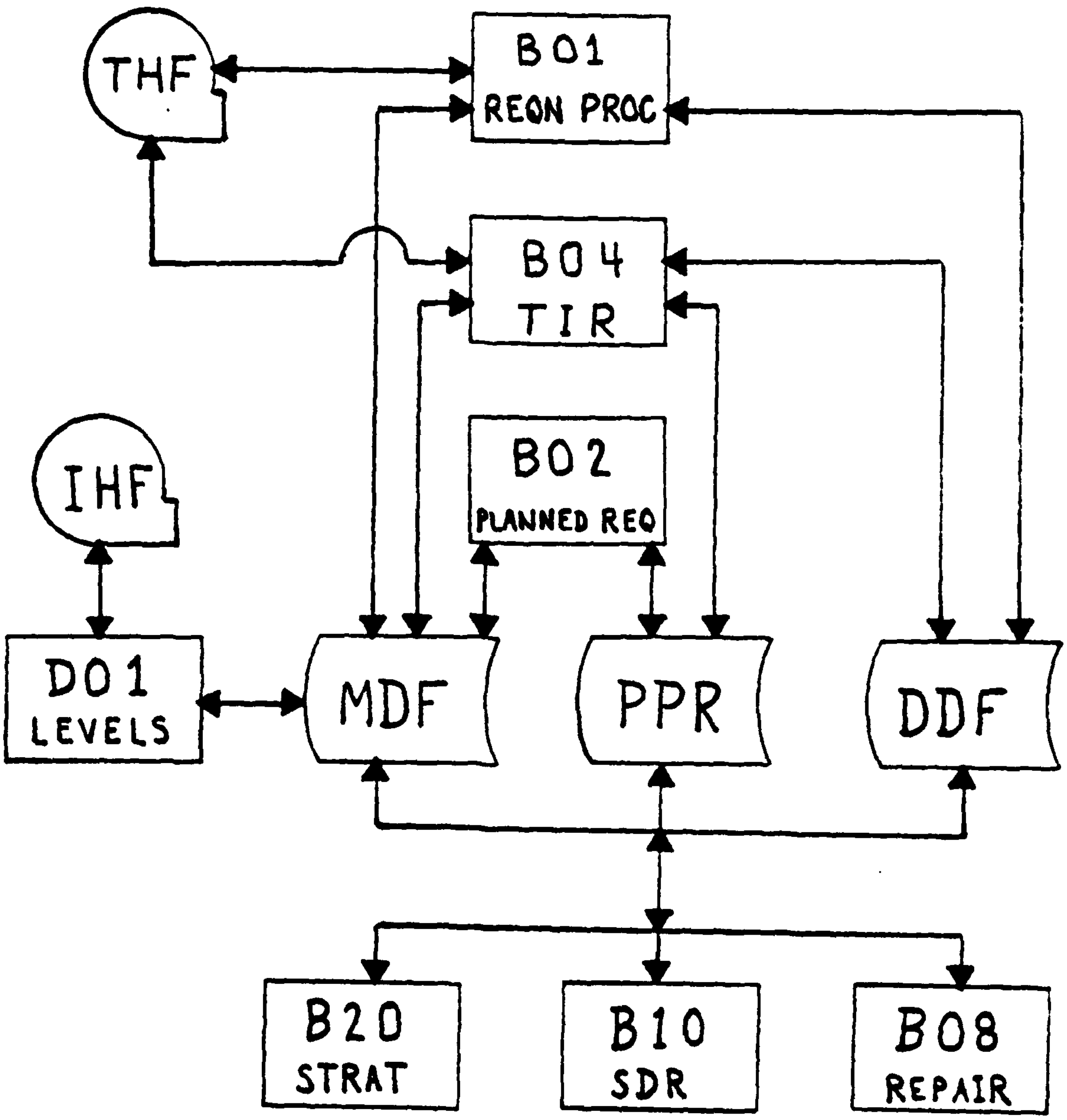

Figure 3

The UICP System [Ref. 2]

graphic display of the relationship between the major UICP repairables files and programs.

The Master Data File (MDF) contains the key data required to operate an inventory control system. Data is filed by National Item Identification Number (NIIN). Information about each item is stored in individually accessed locations called data element numbers or DEN's. Each NIIN has approximately 400 accompanying DEN's that contain such information as current inventory position, demand and carcass return observations for the current quarter, demand and carcass return forecasts, procurement and repair lead times and turnaround times, dimensions, weight, standard and replacement prices, packing and preservation information, etc. The MDF is accessed via real-time data retrieval.

The Planned Program Requirement File (PPR) keeps track of all known requirements (also called non-recurring demands) for RFI assets based upon requests from HSC's, industrial activities, customers and item managers. The PPR can be accessed in real time.

The Due-in/Due-out File (DDF) tracks every outstanding supply action until its completion or termination. It follows ICP directed issues and expected receipts (such as carcass returns once a repairable item has been issued to a customer). It also tracks incoming RFI assets from both repair and procurement, the redistribution of assets among stock points and DOPs, and items going into and out of the Repair Phase. The DDF can also be accessed in real time.

The Transaction History File (THF) contains all the transactions recorded at the ICP over the preceeding two year period. It lists each transaction individually by document number and provides a source of historical data for demand observations, carcass returns, procurement lead times, and repair turnaround times. This file is on tape and can only be accessed through batch processing.

The Inventory History File (IHF) is also a tape file that is accessed by batch processing. The IHF contains demand and carcass return observations for the previous eight quarters as well as inventory position quantities, lead times and turnaround times.

C. THE TIR SYSTEM

The discussion will now focus on the UICP programs that access the data files described above and will explain how they relate to carcass return forecasting. First, it is important to understand the Transaction Item Reporting (TIR) system. If the repairables system can be thought of as a wheel with the repairable item moving around the rim and the ICP at the hub, the spokes of the wheel represent the TIR system. The TIR system is an information system that informs the ICP of every change in status of one of its wholesale system assets. That change in status can include receipts of due-ins, carcass turn-ins, issues of RFI items, forwarding carcasses for repair, and inductions of carcasses into repair. TIR reports are sent via AUTODIN or message. At the end of each day an "accounting" is made of all transactions at a TIR activity and the transactions are TIR'ed to the ICP to update the asset position on all inventory control records. The commands that report daily to the ICP are referred to as being on the "wheel" and are called TIR reporting activities (stock points, industrial activities, some air stations and some mobile logistic support force ships). The ICP's also do business with non-TIR activities which are, in general, commercial DOP's. When a repairable item is sent to a non-TIR activity a due-in is established in the DDF and a blackout of information for that particular item is experienced pending its return to a TIR activity. Non-TIR activities do provide monthly inventory position reports to the ICP, but the information is not available in real time like the TIR. The progress of a repairable item is followed through the system by the item's condition code which is reported via TIR. The following condition codes [Ref. 3] generally apply to repairables:

Condition Code	Status
A	Serviceable (Issuable W/O Qual)
F	Unserviceable (Repairable)
H	Unserviceable (Condemned)
M	Suspended (In Work)

When a carcass is turned in by the customer it is listed as being in "F" condition. When that item is inducted into repair by a TIR reporting DOP, the condition code is changed to "M". If the carcass is sent to a non-TIR reporting DOP, it is reclassified "M" condition when it is forwarded from the last TIR reporting activity. If the carcass is declared irreparable, a TIR reporting DOP sends a TIR to the ICP changing the condition code to "H" and the item is deleted from the appropriate files. Non-TIR reporting DOP's notify the ICP via the monthly report and the ICP manually makes adjusting entries. Once the Repair Phase is completed, the RFI asset is forwarded to a stock point and the condition code is upgraded to "A" condition. Thus, the status of a particular repairable item at any point in the repairables pipeline can be pinpointed by its condition code.

D. UICP PROGRAMS

UICP program B04 processes the TIR's sent to SPCC. The program receives the TIR's and updates the MDF, DDF and PPR files. Additionally it accomplishes the following:

a) calculates lead times for repair and procurement;

b) accumulates demand and carcass return data;

c) accumulates repair inductions, regenerations and disposals; and

d) generates follow-up inquiries on DDF overdue records.

UICP program B01 is the requisition processing prog: . . When a requisition is filled at the point of entry unde. the Area Supply Support Concept, the resulting issue is processed at the ICP through B04. If the stock point is out of stock or the item is not carried, the requisition is TIR'ed to the ICP and processed by B01. This program bumps the requisition against system-wide stock availability and the requisition is then either passed by TIR to another stock point for issue or a backorder is created in the Document Status File (DSF). Then, the program provides status on the demand to the originator, updates the MDF with a demand observation, and establishes a due-out in the DDF.

B02 is the Planned Requirements program and is used to update and manage the PPR file. This program works only with non-recurring demand such as initial outfitting, allowance increases, and planned overhauls. B02 keeps track of known upcoming system needs and ensures that they are taken into consideration as requirements when economic order quantities and reorder levels are computed.

E. THE LEVELS PROGRAM

The cornerstone of the UICP system is the Cyclic Levels and Forecasting program D01. The Levels program computes economic order and repair quantities as well as reorder and repair points. This program determines when to buy or repair and how much to buy or repair. The Levels program is run quarterly and represents the budget execution strategy of management through the establishment of inventory stocking objectives. The goal of the Levels program is to set the proper inventory stocking and reorder levels to maximize Supply Material Availability (SMA) at the minimum possible cost. SMA represents the percentage of the time that a requisition is filled by the supply system when it is initially submitted. The current system-wide goal established by the Naval Supply Systems Command (NAVSUP) is 85 percent. The costs to be minimized are the total variable costs associated with an inventory system - ordering, holding and stockout costs. An outline of the Levels program for repairables follows.

1. The program draws its data base from the MDF.
2. It sets the parameter values for the various calculations. These parameters include the minimum or maximum risk factor depending upon the item's MARK classification (which will be discussed below); the storage cost; and the specific probability distribution to be used in the reorder point calculations.
3. It forecasts the recurring demands and carcass returns and updates estimates of the repair survival rate and the repair and procurement turnaround times.
4. It calculates the economic order quantity, reorder level, economic repair quantity, and repair level.
5. It stores the new calculations, forecasts and average updates in the MDF and the IHF.

When determining the reorder level for an item, the Levels program selects from three probability distributions based upon the item's MARK classification and demand pattern. When demand is very low or the item is held only for safety stock, the Poisson distribution is used to predict lead time demand patterns. For medium demand items, the negative binomial distribution is used and for high demand or fast moving items the normal distribution is used.

As mentioned above, establishment of key inventory parameters, or knob setting, also is dependent upon the MARK classification of an item. Figure 4 illustrates the MARK classification system. The MARK system classifies inventory items based upon demand pattern and unit costs. An item with little or no demand would be designated MARK 0, while an item with low cost but fast moving demand would be designated MARK II, etc. Repairable items are all treated as MARK II AND IV items for UICP calculations.

The UICP models for calculating economic order quantities (EOQ) and reorder points are, in general, modifications of classical inventory formulations as discussed in Hadley and Whitin [Ref. 5] and implemented into the Department of Defense by [Ref. 6]. The following discussion will outline the equations used by the Levels program. The derivations of the models are presented in [Refs. 7, 8].

The repairable procurement model attempts to minimize the variable costs associated with holding inventory. These costs are the ordering costs which include the administrative cost of placing an order; the holding cost which includes opportunity cost of capital, obsolescence

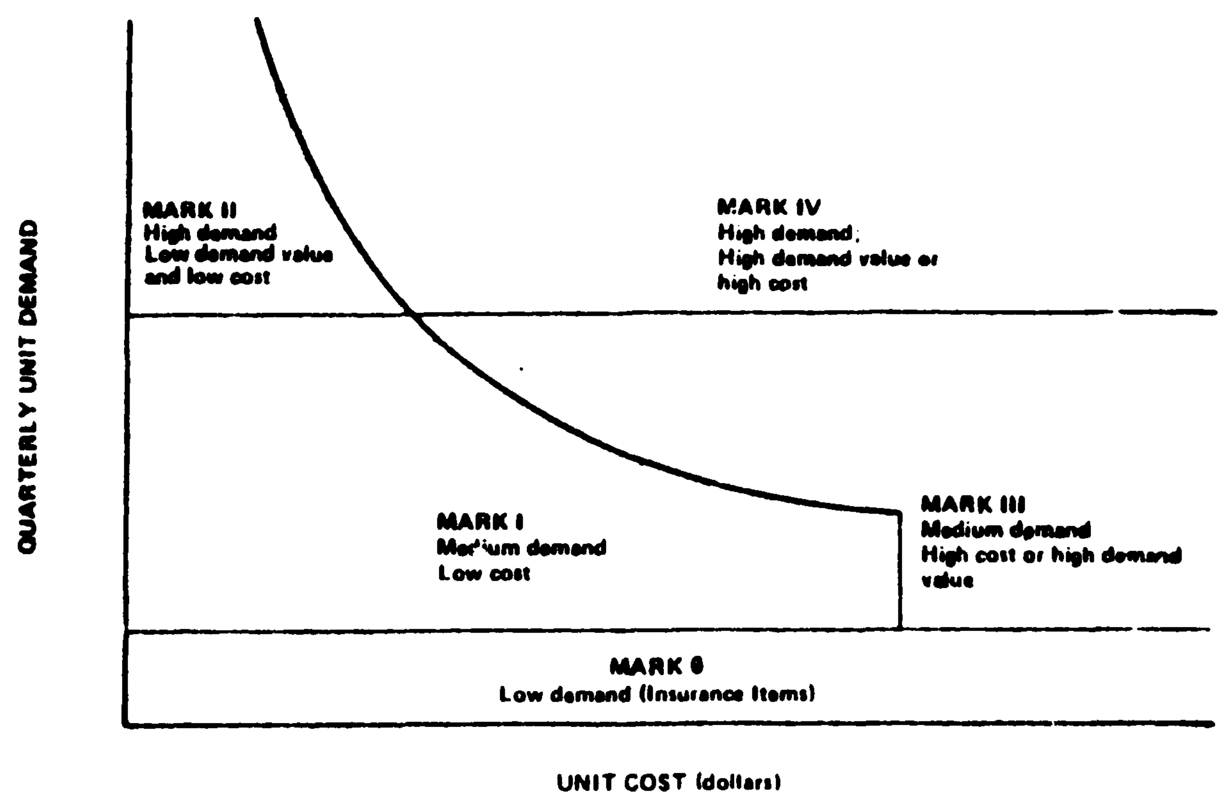

Figure 4

The UICP MARK System [ref. 4]

and storage costs; and shortage costs. The shortage costs are the costs to the supply system of being out of stock for an order. While in the closed military supply system this cost is not quantifiable in terms of dollars and/or material readiness, a shortage cost is imputed as a result of the budgeting process. The initial calculation is the standard Wilson EOQ calculations, Q_w, (modified appropriately for the repair problem) of

$$Q_w = \sqrt{\frac{8\ A\ (D - B)}{I\ C}}$$

where: A = ordering costs,

B = repair reqenerations,

C = *replacement cost for the item,*

D = recurring demand for the item, and

I = holding cost rate.

The "8" in the equation transforms the calculation into a yearly cost since the input variables D and B are quarterly rates. The calculation (D-B) represents "attrition" demand, or the anticipated recurring demand observations that cannot be filled by the repair process. B is the product of the carcass return forecast and the repair survival rate. The repair survival rate (RSR) is an estimate of the percentage of carcasses entering the repair process that will survive and be placed in "A" condition by the DOP. Thus, through the parameter B, the carcass return forecast (CRF) plays a key role in the determination of the order quantity. If the CRF is too high, projecting that more carcasses will be turned in by customers than will actually be the case, then the EOQ quantity will be too low. This will cause too few RFI units to be procured and possibly result in a not-in-stock position. This will drive SMA down and force repairs on existing carcasses at premium prices in terms of both unplanned repair contracts and high priority transportation costs. Alternatively, if the CRF is too low, more carcasses will be returned than estimated. This results in a long-supply position due to inflated buy quantities and greater than expected carcasses returned. While SMA should be high in this situation, the penalty cost will be an excessive investment in inventory and associated greater than necessary holding costs.

The Levels program does not automatically make the EOQ value the buy quantity, but imposes several constraints on the quantity to protect against inordinately large or small buys. This guards against possible obsolescence on a long supply position and an increased purchasing workload for small EOQ's. The actual buy quantity, Q*, is determined

$$Q^* = \text{Max}\ (1,\ (D - B),\ \text{Min}\ (Q_W,\ 12\ (D - B))).$$

The reorder point (RP) is taken to be the sum of the procurement problem variable and a safety level. The procurement problem variable, Z, represents the net assets (RFI) required to meet anticipated recurring demands over the procurement lead time period. It is calculated as

$$Z = (D \times L) - (B \times L) + (B \times T) \quad ,$$

where: Z = procurement problem variable,

L = procurement lead time in quarters,

T = repair turnaround time,

D = anticipated recurring demand per quarter, and

B = repair regenerations.

The safety level is a function of risk and the variance of the procurement problem variable.

Risk, as used in the UICP repairable model, is defined as:

$$RISK = \frac{Q^{*}\ I\ C\ D}{(Q^{*}\ I\ C\ D) + (4\ \lambda\ E\ F\ (D - B))} \quad ,$$

where: E = military essentiality weight,

F = mean quarterly requisition forecast,

Q*= constrained order quantity, and

λ = assigned shortage cost per requisition.

This is the UICP approximation of the classical inventory model of risk which yields the probability of running out of stock over the procurement leadtime period. The CRF is represented in the risk calculation in the repair regeneration factor. If the risk factor is low, the reorder point will be relatively high resulting in frequent reorders and a high safety level. If the risk factor is high, a relatively low reorder point results with a small safety level. If the CRF is low (more carcasses are returned than expected) the risk factor will be smaller than it should be. This causes reorders to occur more frequently than they should thus leading to a higher investment in safety stock than would be actually necessary. On the other hand, a CRF that is too high would result in the opposite situation of a dangerously low safety stock level and probable stockouts.

The other repairables inventory control calculations made by the Levels program are the economic repair quantity (ERQ) and the repair level, both similar to EOQ and reorder quantity. The UICP system, however, considers the repairable EOQ and ERQ problems as separate entities and the calculations are "uncoupled", i.e. the calculation of one does not affect the calculation of the other. The repairable EOQ model, in fact, assumes that the CRF will indeed be accurate and the inductions into the Repair Phase and the subsequent regenerations at the end of the repair cycle will occur on time with certainty.

The ERQ is determined as a function of the variable costs involved in repairing a carcass: cost to place a repair order, holding costs per unit, and backorder costs when there is a shortage of RFI assets and is subject to several system constraints. A formulation similar to the Wilson EOQ model is used to obtain the approximation of the repair quantity, Q_{wr},

$$Q_{wr} = \sqrt{\frac{8\ A_r\ \mathrm{Min}\ (D,\ B)}{I\ C_r}}$$

where: C_r = repair cost for an item, and

A_r = cost to initiate repair action.

Note that the repair quantity equation takes on a slightly different form. If the forecasted demands are less than the forecasted repair regenerations, the forecasted demand figure will be used in the ERQ calculation and there would be no purchase of new units since repair will be able to meet all expected demands. If the forecasted demands exceed the expected number of repair regenerations, B will be used, and there should be a resulting procurement action.

Because of the economics of placing repair orders and/or repairing too many carcasses at one time (again possible obsolescene), there are constraints placed upon ERQ by the Levels program.

$$ERQ = \mathrm{Max}\ (1,\ Q_{wr},\ RVC \times B) \quad ,$$

where: Q_{wr} = optimal Wilson ERQ determination above, and

RVC = repair cycle length in quarters.

The repair level represents the predesignated carcass inventory level that should trigger a repair order being placed for a quantity of ERQ units to preclude running out of stock. This level is a function of the mean and variance of repair turnaround time and the assumed probability distribution of repair leadtime and risk. The repair turnaround time mean and variance parameters are determined by the Levels program from historical data. The probability distributions used are the three previously mentioned.

Risk in the repair quantity calculation is determined by

$$\text{RISK} = \frac{Q_r^* \ I \ C_r \ D}{(Q_r^* \ I \ C_r \ D) + (4 \ \lambda \ E \ F \ B)}$$

where: $Q_r^* = \text{ERQ}$.

The carcass return forecast can cause problems in initiating repair inductions. When the CRF is too high, the risk will be relatively lower. This means a higher repair level. Since the repair order will not be initiated until that level is reached, an order will be delayed awaiting needed carcasses which are returning at the actual lower return rate. This may result in the repairable pipeline "running dry" before more carcasses are inducted with the resulting shortfall in RFI assets from the repair cycle. If the CRF is too low the opposite effect will occur with more money

money being spent on repair than is necessary to maintain the desired SMA.

F. SUPPLY DEMAND REVIEW

In order to implement a "continuous review" model in an inventory system, the system's assets and requirements must be tracked. This is accomplished within the UICP system by the Supply Demand Review (SDR) B10 program. The Levels program provides the reorder levels and reorder quantities as inputs to SDR. Besides the reorder quantity and reorder level for an item, SDR requires two other parameters - total assets and requirements. Total assets for an item include current on-hand and anticipated due-ins within the procurement lead time from both repair (which includes forecasted carcass returns) and procurement sources. Total requirements include planned program requirements, war reserves, anticipated recurring demands and backorders due-out during the procurement cycle. SDR compares assets against requirements to determine the net asset position. If the net asset position is at or below (asset deficiency) the reorder point, a buy recommendation is initiated. This buy quantity is the economic order quantity plus the asset deficiency quantity. SDR is run approximately once a week. It does not review the asset position of every item on each run, but only the items flagged by the TIR program B04. B04 compares the SDR reorder point to the item asset position as determined from the MDF and PPR files and flags the candidate items for processing by SDR.

SDR buy computations can be run in two modes, live or dead. A live SDR buy recommendation is automatically routed to procurement for action unless the item manager manually overrides the system. If a dead SDR is made for an item, the buy recommendation is routed to the item manager who must then decide if the buy should be submitted to procurement. In general, the mode is determined by fiscal constraints. SDR also determines the allocation of the buy quantities and/or redistribution of existing stocks among the stock points. The SDR procedure is graphically illustrated by Figure 5.

G. REPAIR SCHEDULING

The repair levels and ERQs determined by the Levels program are used as the decision parameters for the Repair Scheduling program B08 which also accesses the MDF, PPR and DDF files for its data base. B08 is run about every two weeks and makes a computation of its asset position to compare to the repair level similar to the computation in the SDR process. B08 then makes its repair induction and redistribution recommendation about NRFI material. When the Repair Scheduling program senses that the system is carcass constrained (short), it alters the Movement Priority Designator (MDP) in the MDF. This eventually

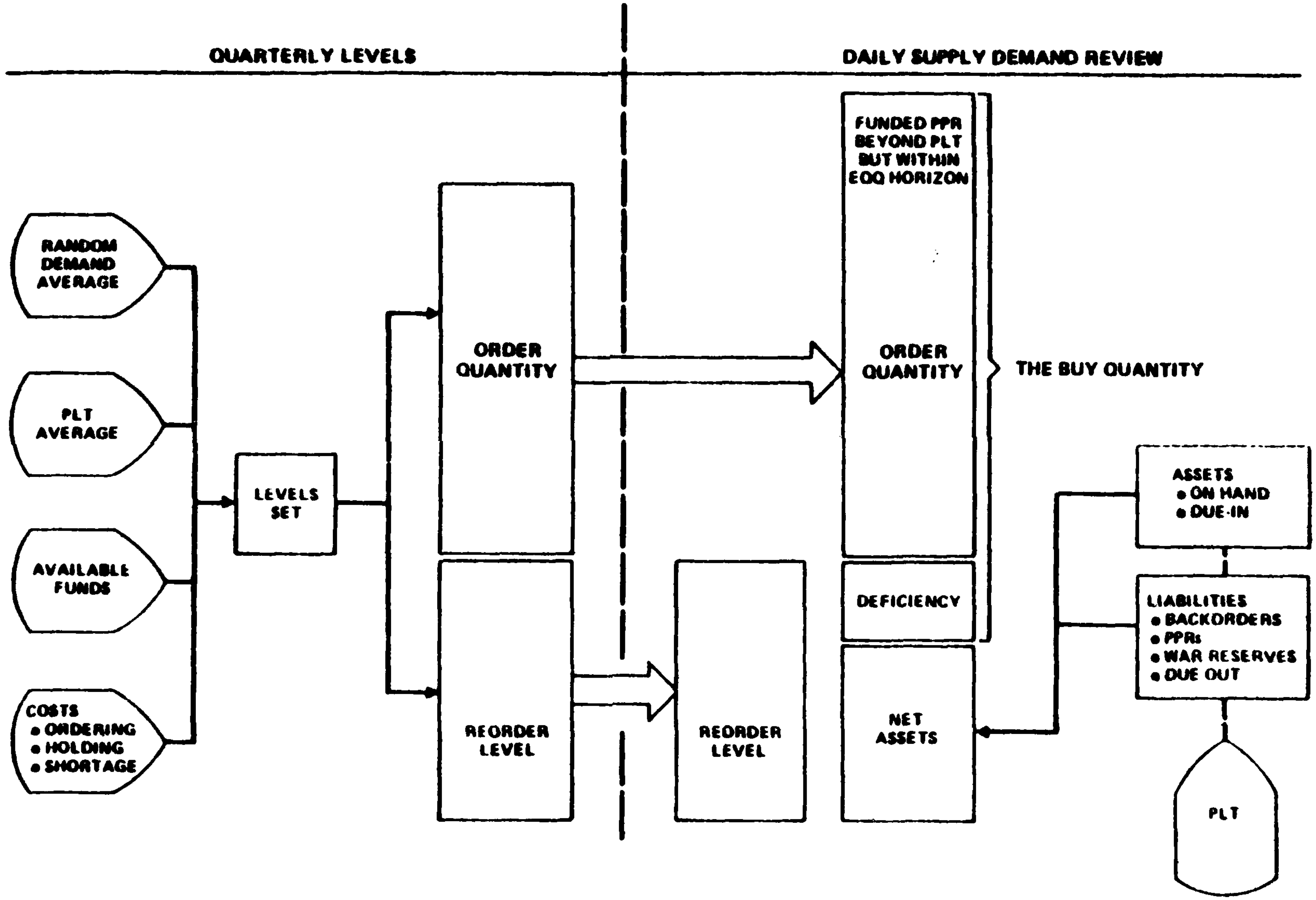

Figure 5
The Supply Demand Review Procedure [Ref. 9]

triggers a change in the MRIL which the customer uses to determine the transportation priority for the carcasses upon turn-in.

H. REPAIRABLES FUNDING

Before considering the repairables funding requirements through the budgeting process of the UICP Stratification program B20, it is important to understand the fiscal structure currently associated with repairables. The Navy divides its material stocks into two major classifications as defined by Wooten [Ref. 10]:

> Principal Items are major assemblies such as aircraft engines, complete radar sets, gun mounts and ammunition. Acquisition of this material is funded by the procurement appropriations - such as OPN, WPN, and APN.
>
> Secondary Items are spare parts, replacement assemblies, and consumable supplies. Examples are tools, repairable assemblies, hardware, fuel, clothing and the like.

Principal items are funded through the appropriations cited, while secondary items are funded through two possible sources. Traditionally, all repairable items were funded by the appropriations accounts that also buy principal items. The other source of funds for secondary items is the Navy Stock Fund (NSF).

The NSF is a revolving fund managed by NAVSUP. This means that the NSF consists of money and/or stock ownership. When stock is issued to customers, the stock portion of the NSF is reduced and the funds portion is increased by an equal amount. These funds are then "available" through the budgeting process to the ICP or stock point to purchase more stock from vendors. This increases the stock in the account and reduces the available cash balance. While in theory this is a closed system, there are losses to the NSF which are the result of material loss, pilferage and transportation charges. These financial losses are made up through surcharges on customer sales. The congressional budgetary process provides the infusion of funds when the NSF operating base is increased due to an enlarged scope of operations. Such an infusion of funds occurred on 1 April 1981 when non-aviation depot level repairables managed by SPCC were changed from APA funding to NSF funding for a three year test period. APA, or Appropriations Procurement Account, funding means that the repairables were procured with funds appropriated annually from the major budget claimants and were essentially free to the repairable item end users. Figure 6 depicts the repairables within the NSF funding picture.

Funding repairables from APA appropriations requires annual budget submissions which are followed by a fixed appropriation to be spent in the designated fiscal year. Under the new system of NSF funding, repairable budgets are also submitted to the NSF manager, NAVSUP, but they are in terms of the obligation authority required to execute an NSF funded operation. The approved NSF budget,

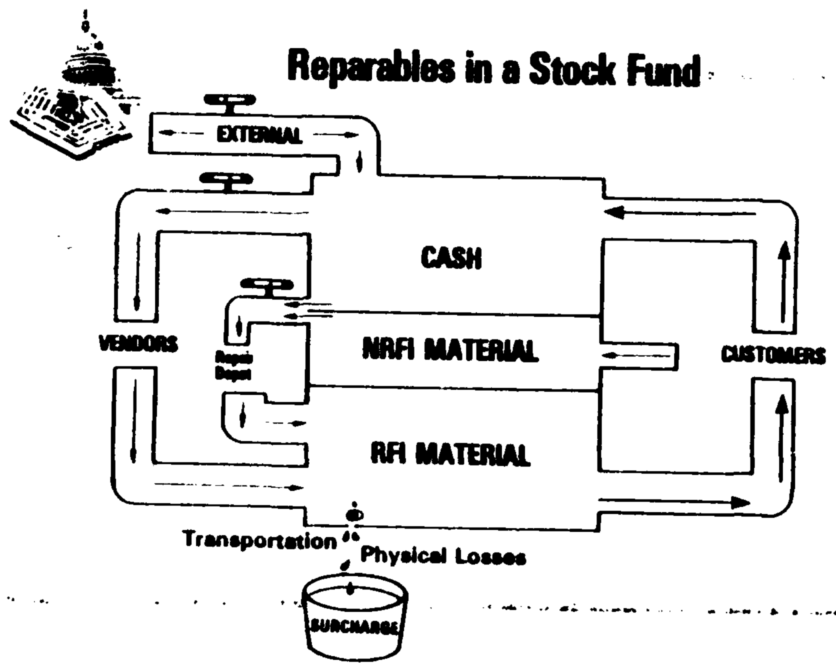

Figure 6
The Repairables Navy Stock Funding Scheme [Ref. 11]

called an approved apportionment, is provided to the recipient in terms of estimated customer NSF sales, NSF obligation authority of the recipient and a deviation (the difference between anticipated sales and obligation authority). NAVSUP then issues the apportioned funds in quarterly allocations.

There are significant advantages of NSF funding over other methods of funding in the repairables area. First, the NSF budget holder can obtain additional obligation authority if sales exceed the anticipated levels originally estimated. The only limitation is that the budget holder's apportionment can be increased only up to a level where there is still the original deviation between obligation authority and the new sales figures. The NSF obligation authority augmentation procedure is therefore simpler than an augmentation request to a specific appropriation account because the justification is automatically provided by increased customer sales. The second distinct advantage of NSF funding of repairables is that the ICP is allowed to decide how to allocate the obligation authority between repair and procurement. Under the appropriation funding procedures, there are separate appropriations for repair and purchase. Therefore, if the CRF is too large when the funds are originally requested, there could be a large reserve of repair money with few carcasses to repair (again carcass constrained) with the purchase funds exhausted early in the fiscal year. If the CRF was too small the opposite situation would occur.

The change in funding of repairables also affects customers from a financial point of view. Prior to 1 April 1981, all non-aviation DLR's were "free" to the customer because of the APA funding. After that date customers were required to pay for RFI units with appropriated funds.

The benefits expected to be derived from the DLR-NSF test are:

(1) improved supply readiness because of more budgeting flexibility,

(2) improved carcass turn-in rates,

(3) more timely turn in of carcasses,

(4) reduction in inventory investments due to improved carcass availability, and

(5) higher fill rate of entry point repairable item requisitions.

Items (4) and (5) are natural consequences of improved carcass turn-in rates. This is to be accomplished through a two-price system for repairable requisitions and an improved carcass tracking program. When a customer submits a requisition for a repairable item, he will be charged a net price which is based upon the repair cost of the item. The net price runs approximately 25-30 percent of the replacement price. If no carcass has been received from an activity seventy-five days after the initial requisition data, an inquiry is sent to the customer by the ICP. If there is not satisfactory follow-up action by the customer or carcass turn-in within twenty-one days after that, the charge to the customer is increased to a full replacement price plus the NSF surcharge cost. This is known as the standard price and is also charged to a customer who does not have a carcass to turn in initially for a recurring demand.

I. STRATIFICATION

The UICP Stratification (or Strat) program B20 determines the budgetary requirements necessary to support the UICP wholesale inventory system. For the repairables operation, B20 estimates these funding requirements as a function of key inventory control variables such as demand forecasts, carcass return rates, RSR, repair prices, replacement prices, procurement lead times and assets available over a two year time horizon. This process then determines the funds required to support the available assets and to procure the replacement units needed to fill the gap between assets and requirements. Strat is run in March and September every year to coincide with the budget cycle and provides the baseline for the procurement and repair budgets submitted by the ICP.

J. CONCLUSION

The above discussion has highlighted the critical role of the carcass return forecast in the repairables inventory control process. The CRF is at the base of both procurement and repair levels computations. While the CRF is only a forecast or "best guess" of anticipated carcasses returning to the repairables cycle, it is important that the forecasts accurately reflect the actual returns. The thesis will now present various forecasting schemes and tests of their effectiveness using actual SPCC data.

III. THE MODELS

The criteria for a good forecasting method is that the model closely follow actual observations and quickly adjust to trends. To do this the model should be closely aligned to the actual underlying process that generates the observed values. To select the appropriate forecasting model, Chambers, Mullick and Smith [Ref. 12] suggest that the following factors be considered:

a) the relevance and availability of historical data,

b) the degree of accuracy desired,

c) the time period over which to forecast, and

d) the cost/benefit of the forecast to the system.

The main consideration is to make the best use of available data. For example, the best forecasting technique available may be prohibitively expensive because of the cost of restructuring the data collection, storage and retrieval systems. Or the best forecasting method may require nonexistent information.

The forecasting technique should be one that achieves system-wide inventory objectives at minimum cost. These costs would consist of the cost to collect the data and actually make the forecast, cost of holding inventories, distribution system costs, the cost of running out of stock, etc. These costs are difficult, if not impossible, to collect and identify in a study of this scope. Therefore, the only MOE's used in this study deal with forecast error measurement. We assume that small forecast errors are consistent with a high level of system supply effectiveness. Also, the cost of data collection and storage used for each technique is not addressed.

This study considers two types of models: autoregressive and causal. An autoregressive model as defined by Makridakis and Wheelwright [Ref. 13]:

> ...is a form of regression, but instead of the dependent variable (the item to be forecast) being related to independent variables, it is related to past values of itself at varying time lags. Thus an autoregressive model would express the forecast as a function of previous values of that time series.

A causal model is defined by Chambers, Mullick and Smith [Ref. 14] as a "model of the system which captures the facts and logic of the situation." The following two sections will deal first with the autoregressive models and then the causal models.

Because of the availability of only eight quarters of data from the IHF, the models are examined over that period of time. The first four quarters are used to generate starting conditions. This obviously limits the models that can be used. Because of the brief amount of data available to develop the model parameters and to analyze forecasting effectiveness, all results of this thesis have to be viewed with caution. The results should serve as the approximate worth or relationship of the forecasting methods on the particular data used. The short time horizon also limits the models that are available for analysis. Time series models like Box-Jenkins, for example, cannot be used.

One further assumption in the use of the following models and the study in general is that the recurring demand forecasting (RDF) technique is reliable. The UICP RDF model used by SPCC is an exponential smoothing model with filters (the same model as described below for carcass return forecasting). The UICP RDF method is discussed in [Refs. 15, 16].

A. AUTOREGRESSIVE MODELS

1. SPCC Exponential Smoothing (SPCC)

The model for forecasting carcass returns currently in effect in the UICP system is exponential smoothing with filtering. The model is:

$$CRF_t = \alpha \times (ACR_{t-1}) + (1-\alpha) \times CRF_{t-1} \quad ,$$

where: CRF_t = carcass return forecast for period t,

ACR_t = actual carcass returns for period t, and

α = smoothing constant.

The forecast for item i for period t is a convex linear combination of the observed carcasses returned in period t-1 and the forecast for period t-1. This method allows the most recent observations to play a key role in forecasting a new value while relying upon the steadying influence of past performance brought forward through the previous forecast. When the new forecast is generated, it replaces the previous forecast. One characteristic of pure exponential smoothing models is that the forecast is slow to catch up with current trends or shifts in the pattern of carcass returns because of the weight of past performance on the forecast. The SPCC model includes filters to make adjustments to the forecast.

The calculations that are used in the filtering process are also determined through exponential smoothing.

$$MAD_t = \alpha \times |ACR_t - CRF_t| + (1-\alpha) \times MAD_{t-1} \quad ,$$

where: MAD_t = mean absolute deviation for period t.

Theoretically, when the population of observations comes from a normal distribution the mean absolute deviation parameter (defined as an expected value) is approximately 1.25 times the standard deviation. It measures the expected absolute deviation of actual carcass returns from the mean. In the SPCC model the mean is replaced by the CRF and expected value is estimated by exponential smoothing. The first filter looks for excessively large or small observations. Limits are set up around the carcass return average or CRF. These limits are six standard deviations or 7.5 x MAD. If the observation for a particular quarter is outside these boundaries, that observation is not used to compute a new CRF, the previous CRF is retained without change (in effect the smoothing constant is set to zero). If the observations are outside the limits in the same direction (either high or low) for two consecutive quarters, a step increase calculation produces the new CRF:

$$CRF_t = \frac{ACR_{t-1} + ACR_{t-2}}{2}$$

and a new MAD is calculated from the equation

$$MAD_t = 1.386 \times (CRF_t)^{.746}.$$

New control limits are established in the following quarter and the procedure continues.

A second type of filter in the SPCC model detects trending, or the tendency of the carcass return observations to be either increasing or decreasing. Trending is tested with the following ratio:

$$\frac{2 \times (ACR_{t-1} + ACR_{t-2})}{ACR_{t-1} + ACR_{t-2} + ACR_{t-3} + ACR_{t-4}}.$$

If the ratio is within the limits [0.9, 1.1], the smoothing constant α is set to 0.1. Otherwise $\alpha = 0.3$. This allows the most current observations to have a greater influence on the CRF. While the CRF will still lag behind au actual trend with $\alpha = 0.3$, the CRF will catch up at a faster rate than when $\alpha = 0.1$.

Because only the current CRF is retained by the UICP system, the SPCC exponential smoothing with filtering program has been included in this project to recreate the forecasts over the two year period this study covers. The program written with the above guidelines to produce the SPCC forecasts is called TSPCC Fortran.

2. Exponential Smoothing (ES)

This model is similar to the UICP exponential smoothing model except that no filtering is involved:

$$CRF_t = \alpha \times ACR_{t-1} + (1-\alpha) \times CRF_{t-1} \quad ,$$

where: CRF_t = carcass return forecast for period t,

ACR_t = actual carcass returns for period t, and

α = smoothing constant.

This model was programmed as TES Fortran. The simulation was run for a complete cycle through the eight quarters for each value of the smoothing constant α ranging from .05 to 1.0 in increments of .05. This was done to provide an indication of which weight α did the best job overall considering the actual SPCC data.

When α = 1.0, the previous observations are eliminated from playing any part in the forecasting scheme. This method is known in the literature as the "naive" forecasting method where:

$$CRF_t = ACR_{t-1}.$$

3. Moving Average (MA)

The moving average forecasting model considers only the past n quarters and gives equal weight to each observation. Unlike the exponential smoothing, the moving average model is not affected by all past observations, but truncates the historical data at a predetermined point.

$$CRF_t = \frac{\sum_{i=1}^{n} ACR_{t-i}}{n} ,$$

where: CRF_t = carcass return forecast in period t,

ACR_t = actual carcass returns in period t, and

n = number of past periods included in the calculation.

The program written to produce moving average forecasts is TMA Fortran. The model was run with n = 2, 3, 4. The fewer the number of quarters averaged, the more easily a trend can be captured. Conversely, if a single observation is an outlier or incorrect, it has a dramatic effect on the forecast. According to Makridakis and Wheelwright [Ref. 17], "the more the randomness, the longer (should be) the moving average." This argues in favor of a longer period being taken into consideration in the averaging process.

4. Moving Least Squares (MLS)

The moving least squares forecasting model is similar to the moving average model in that the current forecast is a function of the last n time periods. The difference is that each point is not given equal weight, but combined by means of the least squares method. Then the least squares line is projected one quarter beyond the input data to arrive at the forecasted value. The algorithm for the moving least squares method is:

$$CRF_t = a + (b \times t) \quad ,$$

where: CRF_t = carcass return forecast in period t,

a = constant or intercept term,

b = slope of regression line, and

t = period number to be forecast.

The input to the least squares formulation to obtain the two parameters is:

$$\begin{array}{cc} \underline{X} & \underline{Y} \\ \begin{bmatrix} 1 \\ 2 \\ \cdot \\ \cdot \\ \cdot \\ n \end{bmatrix} & \begin{bmatrix} ACR_1 \\ ACR_2 \\ \cdot \\ \cdot \\ \cdot \\ ACR_n \end{bmatrix} \end{array}$$

where X is the explanatory variable and Y is the dependent variable. The n represents the number of periods included in the calculation. For example, if the method was predicated upon the previous four quarters, n would equal 4.

Once the least squares line has been determined, the forecast is obtained by setting $t = n + 1$. The parameters for the least squares procedure are determined as follows:

$$b = \frac{n \times \left(\sum_{i=1}^{n} (X_i \times Y_i)\right) - \left(\sum_{i=1}^{n} X_i\right) \times \left(\sum_{i=1}^{n} Y_i\right)}{n \times \left(\sum_{i=1}^{n} X_i^2\right) - \left(\sum_{i=1}^{n} X_i\right)^2} \quad \text{and}$$

$$a = \frac{\sum_{i=1}^{n} Y_i - b \times \left(\sum_{i=1}^{n} X_i\right)}{n}$$

Makridakis and Wheelwright [Ref. 18] discuss the least squares approach:

> This approach to estimating the parameter values in an equation minimizes the squares of the deviations that result from fitting that particular model. For example, if a trend line is being estimated to fit a data series, the method of least squares estimation could be used to minimize the mean squared error. This would give a line whose estimated values would minimize the sum of squares of the actual deviations from that line for the historical data.

The model was run with n = 2, 3 and 4. One advantage of this method is that it detects trends rapidly. This, however, could be a drawback if some of the data points were spurious. The larger the value of n, the slower the least squares model will be to recognize new trends and the less sensitive the model will be to bad data.

The program written to calculate the least squares forecast is TMLS Fortran. An example of the moving least squares method is provided as Appendix A.

5. Adaptive Response Rate (ARR)

The adaptive response rate model is suggested by Makridakis and Wheelwright [Ref. 19]:

> Adaptive-response-rate single exponential smoothing (ARRSES) has an advantage over single exponential smoothing – it does not require specification of a value for α. This characteristic is particularly attractive when several hundreds or even thousands of items require forecasting. Additionally, this method can change the value of α, on an on-going basis when changes in the pattern of the data have made the initial α value no longer appropriate. ARRSES is adaptive in the sense that the value for α will change automatically when there is a change in the basic pattern requiring a different α.

This particular method appears suited to the SPCC forecasting situation with such a variety of items managed. The algorithm for the adaptive response rate model is:

$$CRF_{t+1} = \alpha_t \times ACR_t + (1 - \alpha_t) \times CRF_t$$

with:

$$\alpha_{t+1} = \left| \frac{E_t}{M_t} \right| \quad ,$$

$$E_t = \beta \times e_t + (1 - \beta) \times E_{t-1} \quad ,$$

$$M_t = \beta \times | e_t | + (1 - \beta) \times M_{t-1} \quad ,$$

$$e_t = ACR_t - CRF_t \quad ,$$

$$0 \leq \alpha_t \leq 1 \quad \text{and} \quad 0 \leq \beta \leq 1 \quad ,$$

where: CRF_t = carcass return forecast for period t,

ACR_t = actual carcass returns for period t,

α_t = smoothing constant for period t,

e_t = forecast error for period t,

E_t = smoothed forecast error for period t,

M_t = absolute smoothed forecast error for period t, and

β = smoothing constant for error terms.

There are two smoothing constants in this algorithm, α and β. For this model β was arbitrarily set to .2. The other smoothing value fluctuates dynamically as described above. This model is predicated on α being allowed to vary based upon the performance of the previous forecasts thus adjusting for trends. The adjustable characteristic of α makes this model different from the exponential smoothing model, and, in a sense, performs a filtering of the data. One drawback is that more information must be stored in computer memory. The program written for this model is TARR Fortran.

B. CAUSAL MODELS

1. Regression

The regression forecasting models tie carcass returns (the dependent variable) to a collection of explanatory variables (the independent variable) such as past period recurring demands. The algorithm takes the familiar form:

$$Y = \beta X + u \quad ,$$

where: Y = dependent variable vector,

X = independent variable matrix,

β = coefficients vector, and

u = stochastic disturbance vector.

The estimating technique used is multiple linear regression. This produces maximum likelihood estimators for the model coefficients when it is further assumed that the stochastic disturbance vector u is distributed as the multivariate normal with zero mean and covariance matrix Ω, i.e.

$$u \sim N(E(u),\ \Omega) = N(0,\ \sigma^2 I).$$

With this model and the above assumptions concerning the stochastic disturbance term and non-stochastic X terms, the coefficients are derived in accordance with the Gauss-Markov Theorem. As Intriligator [Ref. 20] points out, the coefficients "are linear and unbiased estimators that are the best of all linear unbiased estimators; i.e. the estimators have minimum variance within the class of linear unbiased estimators."

The coefficient vector solution becomes:

$$\hat{\beta} = (X'X)^{-1} X'Y.$$

The carcass return forecast, $\hat{Y}$, is taken to be

$$\hat{Y} = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots \beta_k X_k.$$

The regression model (coded as TREGRESS Fortran) was used with two different types of explanatory variables, recurring demands and requisition advice codes. All regressions were run on the IBM 3033 VMS batch processing system using the Statistical Analysis System (SAS) to accomodate the large X data matrix (30,044 x 2). SAS allowed the regressions to be calculated with or without intercepts, and it provided R^2, standard errors of regression, Durbin-Watson statistics, t-statistics and various other statistics that are helpful in evaluating regression models.

a. Recurring Demand Regression Models

The first set of regression models uses aggregate demands per period as the independent variable. The general model is:

$$CRF_t = \beta_o + \beta_1 RDF_t + \beta_2 ARD_{t-1} + \beta_3 ARD_{t-2} + \ldots\ldots,$$

where: CRF_t = carcass return forecast in period t,

RDF_t = recurring demand forecast in period t,

ARD_t = actual recurring demand in period t,

β_o = intercept term (when included), and

β_i = weighting coefficient for the ith independent variable.

As discussed in the introduction, a carcass return does not occur unless there is a demand (i.e. a unit has failed thus setting the repair cycle in motion). The date of the demand and the receipt of the carcass, however, do not necessarily coincide. The carcass could be turned in with the requisition for the replacement item or turned in at some later date. This is the relationship that the regression model attempts to identify. The situation is further complicated by the fact that not all carcasses are turned back in to the system. Therefore, the cumulative total of carcass returns over time should be less than 100 percent of total demands over that same period.

It is important to note that some carcasses are turned in with the demand. This means that a carcass return forecast for period t should include some carcasses that resulted from actual demands also in period t. Since the demands for period t are a random variable, they must be forecasted as an input to make the CRF model work (where the coefficient of the current quarter explanatory variable is other than zero). When those resulting regression models were synthesized, the recurring demand forecast was used to estimate carcass returns for the current period. The recurring demand forecasting scheme used was the UICP model SPCC currently employs. This model is identical to the exponential smoothing with filtering model used by SPCC to calculate carcass returns.

The regression model for forecasting carcass returns based upon recurring demand was suggested by SPCC Code 340 and was proposed by SPCC Code 346 as an "offset" model.

b. Advice Code Regression Models

The regression model was also used to investigate the use of advice codes as explanatory variables. Each requisition has an advice code which provides amplifying information on the transaction. The advice codes that apply to recurring demands as defined below are taken from [Ref. 21].

5A - Replacement certification. Requested item is required to replace a mandatory turn-in repairable which has been surveyed as missing or obviously damaged beyond repair.

5G - Exchange certification. Requested item is a mandatory turn-in repairable for which an unserviceable unit will be turned in on an exchange basis under the same document number as that used in the requisition.

5S - Remain-in-place Certification. Requested item is a mandatory turn-in repairable for which an unserviceable unit will be turned in on an exchange basis after receipt of a replacement (serviceable) unit. Turn-in will be on the same document number as that used in the replacement requisition.

5X - Stock replenishment certification. Requested item is required for stock replenishment of a mandatory turn-in repairable for which unserviceable units have been or will be turned in for repair.

To summarize, the 5A advice code means that the requisition does not have a turn-in. These demands will not be included in the explanatory variable matrix since they do not account for any carcass returns. 5A requisitions represent a portion of the recurring demands used in the previous regression model that do not generate a return, thus part of the cause of the ratio of carcass returns to recurring demands being less than one. Advice code 5G indicates that a carcass will be returned at the same time the requisition is submitted. While this does not always occur, the majority of 5G carcasses should return within one period of the original demand. The 5S advice code indicates that the failed part will remain installed in the next higher assembly which will continue to work in some degraded manner until the replacement item is received. At that time the failed unit will be pulled from the assembly and returned to the supply system. The 5S advice code item then essentially assumes the turn-in pattern of normal advice code 5G requisitions. The fourth advice code, 5X, indicates that an intermediate level maintenance facility (e.g. a tender or shipyard) has issued the repairable item from its inventory to the customer and that it is ordering to replace the stock. The 5X, in effect, "masks" the true recurring demand advice code which cannot be determined from the 5X requisition. This creates two problems. One is that the carcass return could vary from no returns to all (i.e. original demand was 5A) to a long wait for the carcass (i.e. original demand was 5S). This makes the carcass tracking program very difficult to implement for 5X demands. The other problem is that the original requisitioner turns the carcass in to the supply system citing the document number of his requisition. The facility that issues the item to the original requisitioner reorders the item for stock using its own requisition number citing advice code 5X. Therefore, the requisition number in the ICP due-in file created as a result of the stock replenishment action and the requisition number on the actual turn-in item do not match. Thus, the issue and subsequent carcass receipt can not be properly paired nor the turn-in waiting times definitely established.

The purpose of regression analysis is to identify the underlying relationship of demands by advice code to carcass returns. Figure 7 illustrates the time-lag layering effect of the carcass returns as a function of recurring demands with a mix of advice codes. An example of the regression model relating carcass returns to demands by advice codes is

$$CRF_t = \beta_o + \beta_1 F5G_{t-1} + \beta_3 A5S_{t-3} + \beta_4 A5S_{t-4} + \beta_5 A5X_{t-3} + \ldots,$$

where: CRF_t = carcass return forecast for period t,

$F5G_t$ = forecasted advice code 5G demands in period t,

$A5G_t$ = actual advice code 5G demands in period t,

$A5S_t$ = actual advice code 5S demands in period t,

$A5X_t$ = actual advice code 5X demands in period t,

β_o = intercept term (if applicable), and

β_i = coefficient for the ith advice code demand in period t-k.

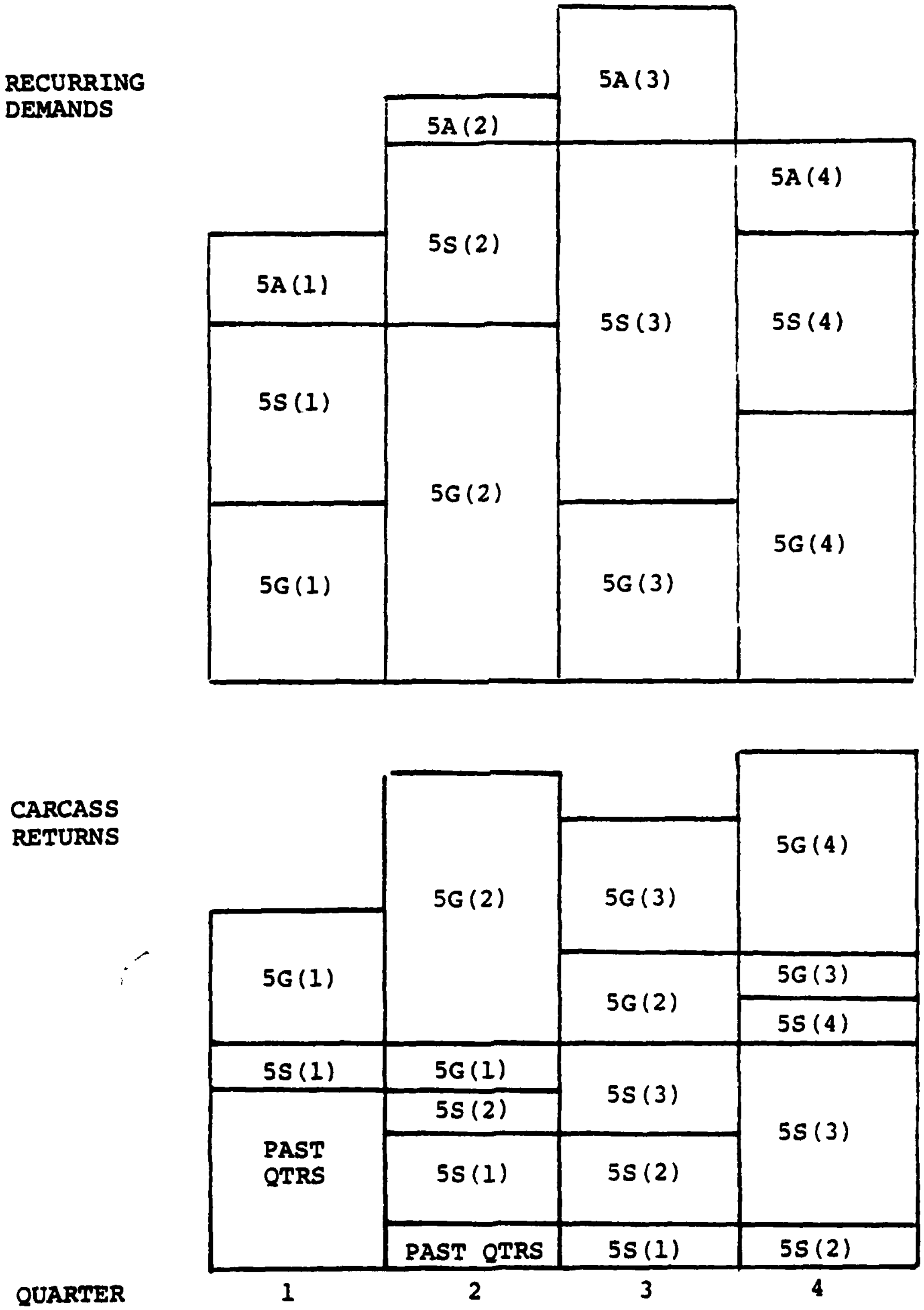

Figure 7. Theoretical Time-Lag Layering Effect of Carcass Returns as a Function of Demands by Advice Code.

2. Time Lag (LAG)

The time-lag model uses the cumulative distribution of carcass returns to predict the number of carcasses returning in any one period. The key element of this approach is to identify the proper distribution of carcasses returning to the system. Information concerning carcass turn-in times has already been collected from the SPCC THF file for a study of the proposed NSF funding of DLR items. The appropriate information from [Ref. 22] is contained in Figure 8 and used to determine the desired carcass return distribution. The data from [Ref. 22] was collected under the following specifications:

> Data for constructing the distributions were extracted from the SPCC Transaction History File for the period November 1975 through October 1977. The time measured is the time between the Julian Date of the document and the transaction date of the TIR. Identification by Atlantic, Pacific and Shore was determined by the Service Designator Code of the document. As a result, any ship issue or turn-in document which was initiated with a Service Designator Code of "N" is compiled under "Shore." Carcass returns were identified by Condition Code "F" in the document. Condition Code "A" turn-ins are contained in "Other Returns." Although a distribution of turn-ins by priority was constructed, very few of the TIR's for turn-ins contained a priority designator.

For the purpose of this study, the cumulative totals of returns by all Service Designation Codes was used because no such distinction is made by the SPCC forecasting models. The data on "Other Returns" was not used.

In order to build the model, the assumption was made that the demands within each of the periods listed in Figure 8

CARCASS RETURNS
DOCUMENT IDENTIFIER D6A

COG: ALL SERVICE DESIGNATOR: TOTAL

	PRIORITY									
	---03---		---06---		---13---		OTHER		TOTAL	
ELAPSED DAYS	NUMBER	$1000	NUMBER	$1000	NUMBER	$1000	NUMBER	$1000	NUMBER	$1000
0-5	1	3	1	1	1	1	6,210	14,594	6,213	14,600
6-10	6	37	1	0	2	1	6,785	14,394	6,794	14,432
11-15	14	41	4	9	3	2	8.795	17,000	8,816	17,052
16-20	25	83	6	7	4	8	8,073	15,708	8,108	15,807
21-30	71	258	32	67	21	49	15,603	33,058	15,727	33,433
31-40	44	152	21	36	21	39	11,339	25,581	11,425	25,511
41-50	37	112	22	42	13	19	8,932	22,038	9,004	22,211
51-60	30	94	13	17	15	17	6,017	16,379	6,075	16,507
61-90	72	291	20	57	33	50	12,200	33,192	12,325	33,591
91-120	40	180	10	22	10	17	7,178	22,018	7,238	22,238
121-150	22	89	14	16	24	35	4,785	14,290	4,855	14,431
151-180	17	74	12	19	8	20	3,154	8,674	3,191	8,788
181-210	14	86	2	2	13	21	2,229	6,067	2,258	6,177
211-240	7	20	1	3	3	1	1,809	5,830	1,820	5,854
241-270	9	31	4	8	2	3	1,421	4,614	1,436	4,656
271-300	7	18	2	7	5	4	1,180	4,167	1,194	4,196
301-330	7	28	2	3	1	8	878	3,037	888	3,078
331-365	3	18	2	7	8	9	920	3,925	933	3,960
366-730	7	29	3	7	6	10	1,557	6,019	1,573	6,066
731+	1	10	0	0	2	5	407	1,685	410	1,700
TOTALS	434	1,655	172	333	195	318	109,482	272,279	110,283	274,586
AVERAGES										
SIMPLE	88.6		87.0		120.9		73.2		73.4	
DOLLAR-WEIGHTED	96.1		89.8		121.9		89.9		90.0	

Figure 8. Cumulative Carcass Returns Over Time.

are distributed uniformly. Therefore, the average demand occurs on the 45th day of the quarter. If a demand occurs very early in the quarter there is a greater chance that a carcass will be returned within the period than if a demand occurs at the end of the quarter. These two situations would tend to net out to the 45 day average available period during the quarter the demand was originally recorded under the uniform demand occurrence assumption. The cumulative distribution function of carcass return waiting times will be partitioned into the following segments:

QUARTER	ELAPSED DAYS
1	0 - 45
2	46 - 135
3	136 - 225
4	226 - 315

Figure 8 does not break at the above "Elapsed Days" end points. The assumption concerning uniformity is again invoked to average the cumulative distribution over the periods in Table I to obtain an estimate of the cumulative probability at the points 45, 135, 225 and 315.

PERIOD	DAY	CUM PROB	DIFFERENCE
1	45	.5584	.5584
2	135	.8537	.2953
3	225	.9335	.0798
4	315	.9696	.0361

TABLE I

CARCASS RETURN DENSITY AND CUMULATIVE DISTRIBUTION TABLE

PERIOD	ELAPSED DAYS	CARCASS RETURNS (X)	f(X)	F(X)
1	0 - 5	6,213	.0563	.0563
2	6 - 10	6,794	.0616	.1179
3	11 - 15	8,816	.0799	.1979
4	16 - 20	8,108	.0735	.2714
5	21 - 30	15,727	.1426	.4140
6	31 - 40	11,425	.1036	.5176
7	41 - 50	9,004	.0816	.5992
8	51 - 60	6,075	.0551	.6543
9	61 - 90	12,325	.1118	.7661
10	91 - 120	7,238	.0656	.8317
11	121 - 150	4,855	.0440	.8757
12	151 - 180	3,191	.0289	.9047
13	181 - 210	2,258	.0205	.9252
14	211 - 240	1,820	.0165	.9417
15	241 - 270	1,436	.0130	.9547
16	271 - 300	1,194	.0108	.9655
17	301 - 330	888	.0081	.9736
18	331 - 365	933	.0085	.9820
19	366 - 730	1,573	.0143	.9963
20	731+	410	.0037	1.0000

Given a recurring demand in period one, the difference column above can be interpreted as being the probability of receiving the carcass back in that same period, the following period and so on. This leads directly to the time-lag model:

$$CRF_t = .5584\ RDF_t + .2953\ ARD_{t-1} + .0798\ ARD_{t-2} + .0361\ ARD_{t-3} \quad ,$$

where: CRF_t = carcass return forecast for period t,
RDF_t = recurring demand forecast for period t, and
ARD_t = actual recurring demand for period t.

The model accounts for only approximately 97 percent of the carcass returns. Because of the four quarter baseline constraint of this study, the model could not include terms beyond t-4. The inclusion of a forecast for recurring demand for the current quarter follows the logic and discussion presented in the regression model. The program used to synthesize this model was TREGRESS Fortran and utilized the SPCC exponential smoothing with filter procedure for forecasting recurring demands.

There are two caveats for this model. First, the model assumes 100 percent carcass returns per demands. The model only addresses time between the occurrence of the demand and the carcass return and not the possibility that there may be no carcass returned for a particular demand.

The other caveat is that the study was conducted before the introduction of NSF funding of repairables. That change, coupled with the improved carcass tracking program, could alter lags between recurring demands and carcass returns.

3. Demand/Return (DEMAND)

Another model analyzed in this thesis was formulated by SPCC Code 790 and sets carcass returns as a function of demand. This approach also incorporates the concepts of repair survival rate (RSR) and wearout rate (WR) into the forecasting procedure. According to [Ref. 23] the repair survival rate is "the percentage of those carcasses that enter the repair process that are returned to RFI condition." The RSR is currently calculated at SPCC through an exponential smoothing process:

$$RSR_t = \alpha \times \left(\frac{IND_t - SUR_t}{IND_t} \right) + (1 - \alpha) \times RSR_{t-1} \quad ,$$

where: RSR_t = repair survival rate in period t,

IND_t = inductions into the repair cycle in period t,

SUR_t = surveys from the repair cycle in period t, and

α = smoothing constant.

The wearout rate is defined by [Ref. 24] to be:

> ...a measure of the fraction of units that is not expected to survive repair. Unlike the Repair Survival Rate, the Wearout Rate considers not only disposals during the repair process but also disposals made prior to the shipment of carcasses to the repair facility. In other words,

disposals made at the intermediate level are included in the computation of Wearout Rate. At SPCC, Wearout Rates are estimated or computed manually and entered into the computer by the technical personnel.

The model is motivated by the fact that the UICP system forecasts recurring demands and carcass returns independently, and the UICP system was designed under the assumptions that all DLR's would be turned in by customers, and that all DLR's turned in by the customers would be inducted into the repair phase of the repairables pipeline.

In reality both situations contain flaws. Carcass returns are not independent of recurring demands but actually a result of demands as detailed in the section on the repairable pipeline. Therefore, the logical approach is to try to tie the two forecasts together. This requires that the differences in the two forecasts be reconciled. This can be done via the WR and the RSR. The RDF includes advice code 5A requisitions (which at SPCC accounts for 8 percent of total recurring demands) which represents DLR's that are not turned in by customers and therefore should not be reflected in the CRF. By including 5A advice code requisitions as a reduction to the WR, this problem is solved. The other key problem is that not all DLR's turned in by customers are inducted into the repair phase before they are surveyed. This results in the RSR being artifically high. By including surveys at the stock points and collection points in both the numerator and denominator of the RSR algorithm, the RSR calculation is more in keeping with its definition. These two adjustments to RSR and WR in theory provide for 100 percent accountability of DLR's and reconciles the RDF to the CRF.

The SPCC-proposed models, as modified by discussion with NAVSUP recorded in [Ref. 25], are :

$$RSR_t = 1 - \frac{\sum_{i=1}^{t-1} (DOPS_i + CPS_i)}{\sum_{i=1}^{t-1} (IND_i + CPS_i)} ,$$

$$WR_t = \frac{\sum_{i=1}^{t-1} (DOPS_i + CPS_i + 5A_i)}{\sum_{i=1}^{t-1} ARD_i} ,$$

$$CRR_t = \frac{1 - WR_t}{RSR_t} ,$$

$$CRF_t = RDF_t \times CRR_t ,$$

where: CRF_t = carcass return forecast for period t,

RDF_t = recurring demand forecast for period t,

CRR_t = carcass return rate for period t,

WR_t = wearout rate for period t,

RSR_t = repair survival rate for period t,

$DOPS_i$ = designated overhaul surveys in period i,

CPS_i = collection point surveys in period i,

$5A_i$ = actual advice code 5A demands in period i,

ARD_i = actual total recurring demands in period i, and

IND_i = carcasses inducted into repair phase in period i.

SPCC recommends that the RSR and WR be kept as cumulative running sums from a predesignated starting point or period, vice exponential smoothed averages. Then, as time goes by, the actual RSR and WR would tend to approach steady state positions. This assumption is good if there is in fact 100 percent accountability of DLR's. If, for instance, carcasses are lost in transit or the carcass tracking program changes the status of a due-in carcass to a 5A advice code demand, the WR and RSR calculations would have to be adjusted accordingly. Otherwise the two calculations might "lose track" over time.

C. SUMMARY

The models presented above represent a variety of forecasting schemes from both forecasting theory and practice. This thesis will examine how these models perform with actual U.S. Navy supply system data. The data itself will be detailed in the next section.

IV. DATA

In order to properly evaluate the forecasting models it was necessary to obtain a realistic data set. Since the model is to be used to forecast carcass returns for active SPCC repairables, the data were gathered based upon criteria built around the real-world system parameters. The following discussion will develop those criteria, detail the collection procedures and sources, and identify some of the problems associated with data collection, transfer and interpretation.

A. DATA SELECTION

The following criteria were used to identify National Item Identification Numbers (NIIN's) to be used in testing the forecasting models:

1. Active items only (i.e. items that have had one or more demands per quarter). The current SPCC model only forecasts recurring demands for active items. Inactive items are not included in the recurring demand budget projections associated with UICP Stratification program (STRAT).
2. Only items with material cognizant (COG's) symbols 7G and 7H. COG's 7G and 7H are defined in [Ref. 26] as non-aviation depot level repairables, both managed by SPCC.

SPCC also breaks the COG's into four digit categories to further stratify demand patterns. The COG's selected were 7Gxy and 7Hxy where X = 0, F or W and y = 1, 2 or 3.

3. Non-family items. A family is defined in [Ref. 27]:

> ...as a collection of two or more items under the cognizance of an ICP that may have a common relationship to each other due to the existence of common applications in higher assemblies, end items, or weapon systems. The relationships between items in a family may vary widely; some items may be completely interchangeable while some items may have to be reworked before they can be substituted for another family member.

The criterion for belonging to a family is basically interchangeability. Because of this the UICP programs assign the sum of these common applications to the item designated "head of the family" or the most common or preferred family member. The levels and forecasting schemes then make their projections based only on these family heads. In the selection of data for the purpose of testing the effectiveness of the various forecasting schemes all family items were deleted from consideration to eliminate potential problems.

4. Item service entry date greater than or equal to 4 years. This is to allow the establishment of a normal pattern of failure and usage data (i.e. minimizing the "bathtub" reliability effect).

5. Only items managed by SPCC Stock Control Division (Code 340). These items represent the mainstream items managed by SPCC that do not require extraordinary management attention such as controlled nuclear related parts.

It was decided not to distinguish between items that were repairable at TIR reporting activities and those repaired at non-TIR reporting activities. As discussed in the section on the TIR system, the UICP information on DLR's repaired at TIR reporting activity is more timely than from a non-TIR activity. Thus time frames are more representative of actual carcass activity and movement. However, the current UICP programs do not distinguish between reporting and non-reporting TIR activities when making forecasts and other inventory calculations.

B. DATA COLLECTION

The above criteria were imposed upon the MDF through a series of utility programs. This resulted in 4292 NIIN's being identified as candidates for testing the forecasting models. This list of NIIN's was then used with other utility programs to extract the desired data from both the IHF and THF. The following table lists the data extracted for each selected NIIN and the source (see Appendix B for a more detailed listing of the data collection parameters):

DATA CATEGORY	SOURCE	DESIGNATION
List of all NIIN's	MDF	MDF
Actual carcass returns	IHF	ACR
Recurring demands	IHF	RD
Designated overhaul point surveys	THF	DOPS
Collection point surveys	THF	CPS

Inductions into repair phase	THF	IND
Assets returned to "A" condition	THF	ACON
Recurring demands by advice code	THF	5A, 5G, 5S, 5X

"A" condition is the condition code for a serviceable item within the supply system. Prior to "A" condition, the item is considered to be in "M" condition meaning it is being repaired.

The data were collected during the period December 1981 - April 1982 and covered only the previous eight quarters. The data were limited to eight quarters because of data breakdown available in the IHF and THF files. The periods covered were:

QUARTER	PERIOD
1	DEC 79 - FEB 80
2	MAR 80 - MAY 80
3	JUN 80 - AUG 80
4	SEP 80 - NOV 80
5	DEC 80 - FEB 81
6	MAR 81 - MAY 81
7	JUN 81 - AUG 81
8	SEP 81 - NOV 81

The data were collected on tape files with one tape per transaction type. Each tape then listed all 4292 NIIN's with the accompanying eight observations representing the summation of all the transactions occurring within each period.

C. DATA MANIPULATIONS

The IHF data tapes supplied by SPCC provided eight quarters of data for each of the 4292 NIIN's. The THF dat tapes contained only NIIN's where there was activity in at least one quarter, and contained only the quarters where there were observation totals greater than zero.

The procedure was to standardize the data files so that all 4292 NIIN's were listed in the sequence of oldest quarter first and most recent quarter last so that the Fortran programs written to run and test the data could accomodate any of the files. To accomplish this, the following steps were taken using a series of utility programs to manipulate the data files:

1. reorder the quarters of the IHF generated tapes by a program designated SORT Fortran,

2. create a file of all 4292 NIIN's from the MDF tape using program NIIN Fortran,

3. expand the THF generated files to include all eight quarters per existing NIIN by placing zeros in the missing quarters and then reorder the quarters as in step 1) through FORMAT Fortran,

4. process the revised THF generated files against the file of all 4292 NIIN's using program AUG-MENT Fortran resulting in a complete 4292 x 8 file, and

5. erase the original files in mass storage and place the revised, ready to use IHF and THF generated files into mass storage.

D. DATA ADJUSTMENTS

A Fortran program (SUMCOLS Fortran) was written to sum the total demands or carcass returns for each individual quarter and then print the results for a quarter-by-quarter comparison of the totals. This was done to highlight for each item any quarter that was grossly out of line with other quarters for either demands or carcass returns. The check revealed the following four situations:

NIIN	1	2	3	4	5	6	7	8	FILE
00-938-3665	3	4	60,010	3	5	1	4	2	ACR
00-937-8496	2	13	15	44,448	0	3	4	3	RD
00-979-4575	34	40	211	6,496	138	63	123	457	RD
00-186-8289	17	0	10,015	10	11	18	21	8	RD

The four large data points (all from the IHF file) were checked by SPCC analysts and all were determined to be bad data. Four new data points were artificially inserted into the data files, with each replacement value selected within the range of existing numbers for the respective NIIN's.

E. DATA CAVEAT

The data used in this study covers the period December 79 - November 81. On 1 April 1981, the funding of DLR's was changed from APA funding to NSF funding as discussed previously. This means that before 1 April 1981, the repairable was basically "free" to customers. After that time the customer was charged for the repairable an amount based upon whether he had a carcass to turn in or not. This funding change was designed to encourage customers to return repairable items into the repairables pipeline by penalizing them for not returning a failed unit. The exact effect this change had on either demand or carcass return data is not explicitly addressed by this thesis, but, in fact, may have exerted a significant impact on the results.

V. OUTLIER ANALYSIS

Outlier analysis is critical to any research that uses real data. Dixon and Massey [Ref. 28] state that there are two types of "bad" data points that we want to either eliminate or be aware of - outliers and incorrect data points. Outliers generally are extreme observations, either very large or very small and can have a substantial effect on any standard regression analysis or standard statistics used to judge the effectiveness of a forecasting method. Outliers and incorrect data points can result from such sources as:

a) human error (i.e. a mistake either in taking the observation or in coding during the man-machine interface phase),

b) data point(s) may be from a population other than the one under consideration, and

c) the population does harbor some abnormally large or small values that have surfaced and are legitimate (i.e. the proposed model of the underlying distribution may not be correct).

Equally important is the possiblity that individual observations of any of the above situations may be present within the range of the bulk of the data and not be recognized by the statistical techniques employed as being "bad".

As discussed in the previous chapter the Fortran program, SUMCOLS, was used to identify gross data elements in the data set. The procedure identified the four erroneous NIIN values discussed in detail in that section. SPCC personnel confirmed that those numbers were indeed wrong and that the possible cause of their existence might have been keypunch or data entry error. With these four numbers corrected the model building and data analysis phase of the thesis began. It was soon apparent that there was a tremendous amount of "noise" in the data.

A Fortran program named CHECK was written to provide a side-by-side listing that matched recurring demands to the actual carcass returns for a particular NIIN over the eight quarters of data. This procedure revealed many NIIN's with data that appeared out of line (i.e. where either the carcass returns were an order of magnitude different, either high or low, from the corresponding demands).

Two examples are listed below:

Centrifugal Pump 00-368-3186

QTR	1	2	3	4	5	6	7	8
ACR	0	0	0	0	0	0	0	7
RD	65	61	92	102	71	129	118	99

Chamber Assembly 00-678-2686

QTR	1	2	3	4	5	6	7	8
ACR	5	24	27	22	116	557	336	301
RD	5	5	6	6	2	1	1	2

SPCC explained that the pump was converted from 1H COG to 7H in April 1981. Before that time the pump was not designated as a repairable and, therefore, not returned to the system for repair. SPCC also explained the anomalous behavior in the chamber assembly data by indicating that the part was being phased out of the system with no substitute or replacement NIIN listed.

Based upon discussions with SPCC personnel the following reasons (not an exhaustive list) were put forward as being possible causes of incompatible data in the ACR and RD files:

1) Upon implementation of the DLR-NSF test on 1 April 1981, there was a moratorium on overdue or extra carcasses. The user could turn in any carcass(es) without reference to a specific demand or requisition number and receive credit for the carcass (this could lead to a cleaning out of workbenches).

2) Possible incorrect coding of requisitions or turn-in documents so that a carcass receipt is not posted against the correct requisition and/or NIIN.

3) Carcass turn in made by a ship going into an ROH where the equipment is deleted from the COSAL with the accompanying spares being returned without corresponding demands.

4) Incorrect coding of a requisition as a non-recurring demand (when it should be recurring). When the carcass is subsequently returned it would be identified correctly as a carcass return, but there would be no corresponding recurring demand.

These types of situations tend to result in imbalances in the ACR and RD totals illustrated by the above two examples. In these situations neither autoregressive nor causal models would be effective in forecasting carcass returns. In addition, causal models built from noisy data could also prove to be a problem. Therefore, it was decided to apply a filtering procedure against the ACR and RD figures for each NIIN and to find a subset of NIIN's whose carcass return and recurring demand patterns and totals were related realistically. In developing the filter, it was assumed that carcass returns and recurring demands are positively related in some manner, and that there are many forces and actions within the supply system that cause outliers or erroneous data points to enter the data files that are not indicative of the underlying relationship of carcass returns to recurring demands.

The purpose of the filter is to eliminate the data points extraneous to the model building process. All the models will then be synthesized using both the filtered and unfiltered data.

The Fortran program OUTLIER was written to implement the criteria outlined in Table 2. The criteria are based on two sums for each individual NIIN: the sum of actual carcass returns and the sum of recurring demands both taken over the eight quarters. The third figure computed is R, the ratio of total carcass returns to total recurring demands. In theory, the ratio of carcass returns to recurring demands over the life of a particular item (i.e. the steady state rate) should be approximately 1.0. In reality many carcasses never make it back to the repair

TABLE II

OUTLIER SCREENING PROCEDURE

REJECTION CRITERIA		$\Sigma RD \leq 50$	$\Sigma RD > 50$
SITUATION	(RATIO)	**DECISION RULE**	**DECISION RULE**
a) $\Sigma ACR > \Sigma RD$		reject if $R \geq 1.50$	reject if $R \geq 1.25$
b) $\Sigma ACR > \Sigma RD$		no rejection unless $\Sigma ACR = 0$ (SEE C)	reject if $R \leq .5$
c) $\Sigma ACR = 0$		reject if $\Sigma RD > 25$	reject
d) $\Sigma RD = 0$ (denominator cannot = 0)		reject	reject
e) $\Sigma ACR = \Sigma RD = 0$		reject	reject

$$\text{RATIO} = R = \frac{\Sigma ACR}{\Sigma RD}$$

cycle (i.e. 5A advice code requisitions and collection point surveys) and in any short-run period carcass returns can lag behind their corresponding demands. These factors would make the ratio R somewhat less than 1.0. The lower bound for R was arbitrarily set at 0.5. The upper bound of R was set at 1.5 for total recurring demands less than or equal to 50. This is to allow for carcasses returning for demands recorded in a period prior to the eight quarters used in the project. For total demands of greater than 50, R was set at 1.25. The cut-off point of 50 was also arbitrary, but selected to allow for two ranges for R since the quotient of a division operation will vary greater with a change in the numerator when the denominator is small.

The program OUTLIER identified 2974 NIIN's as acceptable; that is, within the bounds as established by Table 2. This represents 69 percent of the original 4292 NIIN's and points out that a significant portion of the data may cause real problems in the implementation of any forecasting model. It also points out that some type of screening or filtering technique should be used to screen the data as is the case with the currently implemented UICP exponential smoothing model.

One final caveat to filtering data is provided by Makridakis and Wheelwright [Ref. 29]. They state that judgment must be used as to when adjustments to data really will improve the accuracy of the forecast and when they will not. The key problem is that filtering also tends to eliminate some of the valid information contained in the data. While adjusting a data set facilitates the use of standard forecasting schemes, the results may not be as reliable with the loss of the outlying but relevant data.

VI. MODEL BUILDING

This chapter deals with the formulation of regression models only. The first section discusses carcass returns regressed on total recurring demands and the second section details regression models with carcass returns as a function of recurring demands by advice codes. All regressions were linear and conducted on the Statistical Analysis System (SAS).

In both cases the procedure was to obtain the parameters for the linear equation by running the regression on as much data as possible. This included data for all eight quarters. Therefore, the parameters were partially obtained by using data that was subsequently used to test those parameters against the MOE's. This overlap only involved the data for the last four quarters. As a result, this procedure will bias the MOE statistics. No attempt was made to identify or measure the bias. It was felt that obtaining regression models using only data from the first four quarters (i.e. eliminating half of an already time constrained data set) would have caused more serious problems than the bias introduced into the MOE's by including all the data.

As discussed in the section on regression models, the model used for regressions was:

$$Y = X\,\beta + u \quad ,$$

where: Y = dependent variable,

X = independent variable,

β = parameters to be determined, and

u = error term.

The following example will illustrate the procedure used to build the input matrix for SAS for all the regression models. Consider the model:

$$CRF_t = \beta_1\, ARD_{t-1} + \beta_2\, ARD_{t-2}.$$

Here the carcass return forecast (or average) is a function of the two previous quarters actual recurring demands (ARD) with no intercept term. Since there are eight quarters of available data, the third quarter carcass return forecast would be a function of actual demands in quarters one and two, the fourth quarter forecast would be a function of demands in quarters two and three and so on. This would correspond to a SAS input matrix configuration as follows:

$$\begin{bmatrix} ACR_3 \\ ACR_4 \\ \cdot \\ \cdot \\ \cdot \\ ACR_8 \end{bmatrix} = \begin{bmatrix} ARD_1 & ARD_2 \\ ARD_2 & ARD_3 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ ARD_6 & ARD_7 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} ,$$

where: ACR_i = actual carcass returns in period i, and

ARD_i = actual recurring demands in period i.

In this case Y, the dependent variable, would be a (6 x 1) matrix and X, the independent variable, would be a (6 x 2) matrix. Since the regression is to be run on all 4292 NIIN's, Y becomes a ((4292 x 6) x 1) or (25,752 x 1) matrix and X becomes a ((4292 x 6) x 2) or (25,752 x 2) matrix. When the regressions for this particular model are run for the 2974 filtered NIIN's, the Y and X matrices would be (17,844 x 1) and (17,844 x 2) respectively. If the CRF is to be a function of the three previous quarters then the dimensions of the individual NIIN's Y and X matrices are reduced by one observation each to become (5 x 1) and (5 x 3) respectively. The full X and Y matrices for both 4292 and 2974 items are correspondingly smaller.

A. RECURRING DEMAND REGRESSIONS

Table III lists the regressions run on recurring demands using all 4292 NIIN's. Table IV presents the regression results using the filtered NIIN's only. Each model is individually identified by an alphabetic character (the ordering of the models does not have any significance). A single character designation (e.g. A) means that the model was a result of a regression on all 4292 items. A double character designation (e.g. AA) indicates that the model was

TABLE III

REGRESSION ON RD (RAW)

Model	Cum.	Intercept	RD	RDM1	RDM2	RDM3	RDM4	R^2	Std. Dev.
A	.6517	.9797	.6517					.4742	21.7620
B	.6564		.6564					.4833	21.7832
C	.7457	.7440	.3642	.3815				.5307	21.2857
D	.7496		.3663	.3833				.5399	21.2980
E	.6752	1.1786		.6752				.4749	22.5149
F	.6809			.6809				.4844	22.5446
G	.7634	.6611	.2550	.2725	.2359			.5427	20.7912
H	.7670		.2564	.2736	.2370			.5519	20.8010
I	.7628	.8244		.2775	.2304	.2549		.5219	21.5759
J	.7674			.2793	.2319	.2562		.5316	21.5907
K	.7581	.5283	.1369	.1953	.1737	.2522		.5505	19.9909
L	.7610		.1376	.1960	.1744	.2530		.5594	19.9971
M	.7348	.8769		.4007	.3341			.5163	21.3806
N	.7395			.4032	.3363			.5258	21.3977

TABLE IV

REGRESSIONS ON RD (FILTERED)

Model	Cum.	Intercept	RD	RDM1	RDM2	RDM3	RDM4	R^2	Std. Dev.
AA	.8399	-.3250	.8399					.8355	11.7111
BB	.8383		.8383					.8381	11.7152
CC	.8983	-.4986	.3233	.5750				.8845	9.9814
DD	.8958		.3219	.5739				.8861	9.9933
EE	.8789	-.3482		.8789				.8650	10.7918
FF	.8772			.8772				.8671	10.7970
GG	.9100	-.5167	.1281	.4233	.3586			.8924	9.5661
HH	.9073		.1270	.4225	.3578			.8939	9.5794
II	.9165	-.4938		.3501	.2993	.2671		.8874	9.8315
JJ	.9139			.3492	.2983	.2664		.8890	9.8432
KK	.9164	-.5039	.0465	.3339	.2865	.2495		.8876	9.8214
LL	.9139		.0454	.3334	.2858	.2493		.8892	9.8337
MM	.9430	-.4378	-.0554	.4093	.2703	.1019	.2169	.9077	8.9979
NN	.9409		-.0565	.4094	.2698	.1016	.2163	.9091	9.0079
OO	.9084	-.4790		.4928	.4156			.8898	9.6798
PP	.9060			.4916	.4144			.8914	9.6911

the result of a regression based upon the 2974 filtered items. The cumulative total column is the algebraic summation of the parameters for each model. This total shows the percentage of recurring demands that are represented by carcass returns for each model. For example, Model A suggests that 65 percent of all recurring demands result in a carcass return. The column "intercept" is the B_o or intercept term in the regression line, "RD" means recurring demands in the current quarter, "RDM1" literally translates to recurring demands minus one (or a lag of one quarter). RDM2 means a lag of two quarters and so on. A blank entry in the column of any one model means that the coefficient of the respective column heading is zero. While all the standard regression statistics were calculated by SAS, only the individual model parameters, the R^2 statistic and standard deviation of each model are displayed. In all cases the F statistic was significant and the Durbin-Watson statistic showed no autocorrelation.

All models were run with and without intercepts. In theory the intercept should be an adjustment factor to the explanatory variables not present in the model. In all cases the intercept term made a relatively insignificant contribution to the forecast.

Table V is a display of the models chosen for synthesis using the SPCC data. Models B and BB were selected because the CRF in period t is represented as a direct function of

TABLE V

REGRESSION MODELS

Designation	Model	Regression Based Upon
B	$CRF_t = .6564\ RDF_t$	Raw Data
D	$CRF_t = .3663\ RDF_t + .3833\ AD_{t-1}$	Raw Data
F	$CRF_t = .6809\ AD_{t-1}$	Raw Data
K	$CRF_t = .5283 + .1369\ RDF_t + .1953\ AD_{t-1} + .1737\ AD_{t-2} + .2522\ AD_{t-3}$	Raw Data
L	$CRF_t = .1376\ RDF_t + .1960\ AD_{t-1} + .1744\ AD_{t-2} + .2530\ AD_{t-3}$	Raw Data
N	$CRF_t = .4032\ AD_{t-1} + .3363\ AD_{t-2}$	Raw Data
BB	$CRF_t = .8383\ RDF_t$	Filtered Data
DD	$CRF_t = .3219\ RDF_t + .5739\ AD_{t-1}$	Filtered Data
FF	$CRF_t = .8772\ AD_{t-1}$	Filtered Data
GG	$CRF_t = -.5167 + .1281\ RDF_t + .4233\ AD_{t-1} + .3586\ AD_{t-2}$	Filtered Data
HH	$CRF_t = .1270\ RDF_t + .4225\ AD_{t-1} + .3578\ AD_{t-2}$	Filtered Data
PP	$CRF_t = .4916\ AD_{t-1} + .4144\ AD_{t-2}$	Filtered Data

the recurring demands also in period t. In practice the recurring demands for the current period are not available until the end of the period, so the CRF becomes a function of the recurring demand forecast as discussed previously. Models F and FF test the hypothesis that the CRF is simply a function of the actual recurring demands in the previous period. This model predicts the carcass returns on the most current, actual observation vice a forecast as in B and BB. This model is similar to the naive forecasting model, but it uses a coefficient other than one. Models D and DD combine the above models to make the CRF a function of both the current quarter's recurring demand forecast and the previous quarter's actual observations. Models L and HH were selected for testing because they have the highest R^2 statistics within their respective data groups. Similarily, models K and GG were selected for the lowest standard deviation calculations. It should be noted that models MM and NN both had more favorable statistics than models GG and HH, but MM and NN were disregarded because in both cases the coefficient of the current quarter's recurring demand was a negative number. Intuitively, the recurring demands in a quarter could not serve to reduce the carcass returns expected to arrive in that period. Models N and PP were selected because of their intuitive appeal. It is realistic to expect that carcasses arriving in period t were generated by demands in period t-1 and t-2. It also is a model that is predicated upon past actual data and does not use any forecasted values. The t statistics of the parameters for all the models listed in Table V were all greater than |2|, thus significant at significance levels of .05 and greater.

It is interesting to note that the regression statistics in Tables III and IV are more a function of the data used to construct the model than the model itself. There was some variance among the statistics within each data set category, but not as significant as between the data sets themselves. When all the data were used the R^2 or coefficient of determination tended to be approximately .5. This indicates that a significant portion of the total variance is not explained by the regression (i.e. the carriers selected). Thus the model does not fit the available data very well. This could cause the forecasts resulting from one of these models in any particular period to vary considerably as seems to be indicated by the large standard deviation statistics. The statistics on the filtered data, as would be expected, show significant improvement. The standard deviation, however, is still relatively high. This could indicate that there are problems with the model or that carcass returns vary widely and are inherently difficult to predict.

B. ADVICE CODE REGRESSIONS

Due to the large number of possible carriers with respect to the advice codes and the SAS data capacity limitations, a subset of the 4292 item data set was used in the regression phase of the advice code model building. A ten percent random sample of the 4292 NIIN's was determined by a program RANDOM Fortran which called upon a computer library subroutine that contained a pseudo random number generator. This procedure is detailed in Appendix C.

Table VI contains the results of the regressions of carcass returns on advice codes. Table VI is constructed in a similar fashion to Tables III and IV with the three categories of advice codes across the top of the display. The star behind a particular number indicates that that coefficient failed the t test (i.e. the t statistic was less than $|2|$). The cumulative distribution column has been deleted. In the case of the regression using recurring demands only, the cumulative total effect could be employed because there was only one general category of explanatory variables. In the advice code model there are three distinct categories.

Regression 9 was used to represent the advice code regression model even though models 1, 2 and 4 had slightly better overall statistics and more significant parameter values as determined by the t statistics. Model 9 was selected over those three because all of them required a

TABLE VI

ADVICE CODE REGRESSIONS

Model	5G	5GM1	5GM2	5X	5XM1	5XM2	5XM3	5S	5SM1	5SM2	5SM3	Std. Dev.	R^2
1	.6852	.8108	.5799				.4700		.2718	1.2709		6.1831	.7086
2	.6666	.8594	.8368				7470		.5195			6.3004	.6973
3	.6803	.8126	.5603				.4120		.2415	1.2339	.2404*	6.1801	.7090
4	.7488	.9589					.5246		.2686	1.4619	.3334	6.2283	.7043
5	.7652	.9723				-.2070*			.2725	1.5597	.4159	6.2359	.7036
6	.6861	1.3086			.1062*				.5058	.9500		6.9144	.6513
7	.7251	1.3074		-.0349*	.1145*			-.1187*	.5576	.9856		6.9145	.6515
8	.6966	1.3051		-.0624*	.1268*				.5156*	.9564		6.9152	.6513
9		1.3935	.8481				.6090		.4738	1.2020		6.4115	.6867

* Indicates failed t test.

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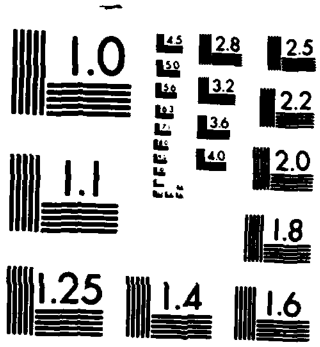

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prediction of advice code demands in the period to be forecast. While there is a recurring demand forecasting procedure, there is no provision in the UICP system for forecasting the number of recurring demands for a period by advice code category. The model selected requires only advice code information that is available from the previous quarters.

VII. EVALUATION CRITERIA

There are a number of measures of effectiveness (MOE's) or evaluation criteria to test any forecasting scheme. Each MOE is unique and will generally identify a specific forecasting technique as superior to the others. However, this does not assure that all MOE's will identify the same method as being optimal. Therefore, five popular MOE's have been selected to test the various carcass return forecasting methods examined in this thesis. The evaluation and comment sections will discuss the merits of each forecasting method with respect to each of the MOE's listed below.

A. MEAN ABSOLUTE ERROR (MAE)

$$MAE = \frac{\sum_{i=1}^{n} | ACR_i - CRF_i |}{n} ,$$

where: ACR_i = actual carcass returns for item i,

CRF_i = carcass return forecast for item i, and

n = total number of items being evaluated.

The range of MAE is zero to plus infinity.

B. MEAN ERROR (ME)

The mean error criterion is divided into two ranges — positive errors and negative errors. This measure shows the bias of a particular method towards either high (positive) or low (negative) forecasts and the magnitude of the biases.

1. Mean Positive Error (MPE)

$$MPE = \frac{\sum_{i=1}^{np} (ACR_i - CRF_i)}{np}$$

for all $ACR_i \geq CRF_i$,

where: np = total number of observations where $ACR_i \geq CRF_i$.

2. Mean Negative Error (MNE)

$$MNE = \frac{\sum_{i=1}^{nn} (CRF_i - ACR_i)}{nn}$$

for all $ACR_i \leq CRF_i$,

where: nn = total number of observations where $ACR_i \leq CRF_i$.

The range of both MPE and MNE is positive and each will be shown separately.

C. MEAN FORECAST ERROR (MFE)

$$MFE = \frac{\sum_{i=1}^{n} (CRF_i - ACR_i)}{n} \quad .$$

This MOE differs from mean absolute error in that all forecasting errors are simply summed with their appropriate signs vice using the absolute values. This results in averaging the positive and negative errors. Thus the range of this MOE is from minus infinity to plus infinity. The optimal forecasting method would presumably be the method with MFE closest to zero. The bias of the method is indicated by the sign of MFE. If MFE is positive, the forecasting method tends to overestimate carcass returns and, conversely, if the MFE is negative it underestimates carcass returns.

D. ROOT MEAN SQUARE FORECAST ERROR (RMSFE)

$$RMSFE = \sqrt{MSE} \quad ,$$

$$MSE = \frac{\sum_{i=1}^{n} (ACR_i - CRF_i)^2}{n} \quad ,$$

where: MSE = mean squared error.

MSE is discussed in detail by Makridakis and Wheelwright [Ref. 30]. MSE and RMSFE are often used because of their similarity to the familiar variance and standard deviation calculations. They differ only in that variance is calculated using the mean of the observations vice the forecasted value (CRF_i).

E. MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

$$MAPE = \frac{\sum_{i=1}^{n} | PE_i |}{n} ,$$

$$PE_i = \left| \frac{ACR_i - CRF_i}{ACR_i} \right| \times 100 ,$$

where: PE_i = percentage error for item i.

This MOE is also detailed in [Ref. 30]. The range of the MAPE is zero to plus infinity. The same weighting is applied to both high and low estimates by a forecasting method.

VIII. MODEL ANALYSIS

The results of the forecasting models synthesized with the SPCC data will be displayed and analyzed in this section. As a result of the outlier screening procedure, the models were run a) with all the SPCC data (identified as "raw" data) and b) only with the data that survived the filtering process (identified as "filtered" data). The results for each forecasting method are listed by MOE and quarter for the period December 1980 - November 1981 in Appendix D. The quarters correspond to the following periods:

QTR	PERIOD
5	DEC 80 - FEB 81
6	MAR 81 - MAY 81
7	JUN 81 - AUG 81
8	SEP 81 - NOV 81

The MOE is listed at the top of the page. The model and the data used to test the model are listed on the left-hand side of the page. The MOE's correspond to those described in the evaluation criteria chapter. The right most column is the average of the MOE's across the row.

The MOE averages are carried forward for evaluation purposes and are displayed in Tables 7 - 11 in this chapter.

For each table the MOE is listed across the top margin with the model designation along the left-hand margin. As in the appendices, the models are separated by the data type, either raw or filtered. The number in each cell represents the average value for the designated model for that MOE over the four quarters measured in Appendix D. The asterisk indicates the best value in each column for a particular MOE. The MOE's are:

MAE - mean absolute error

MFE - mean forecast error

RMSFE - root mean square forecast error

MAPE - mean absolute percentage error

MPE - mean positive error

MNE - mean negative error

"No." Indicates the number of observations that made up either MPE or MNE, whichever it follows.

A. REGRESSION MODELS (REG)

Table 7 summarizes the results for the regression models. The letter designated a particular regression model is keyed to the model as defined in the model building chapter.

For the models run against all the data, Model B was superior to all the others except in the category MPE where model FF was better. Models B and FF are similar in that the CRF is simply the function of one explanatory variable

TABLE VII

REGRESSION MODEL RESULTS

RAW DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
B	5.065*	.383*	77.225*	116.211*	4.816	2411	5.281*	1881
D	5.531	-0.641	112.331	133.638	4.693	2232	6.260	2060
F	5.781	-0.435	135.426	130.734	4.029	2862	9.195	1430
K	6.247	-1.674	129.678	182.163	8.644	1121	5.314	3171
L	6.043	-1.170	130.127	155.212	4.749	2190	7.336	2102
N	6.069	-1.086	140.622	163.495	4.358	2455	8.337	1837
BB	5.416	-0.894	96.331	143.157	4.396	2186	6.353	2106
DD	6.091	-1.842	140.762	159.091	4.412	2065	7.492	2227
FF	6.470	-1.999	169.278	163.450	3.527*	2739	11.591	1553
GG	6.589	-1819	158.357	192.081	3.769	2714	11.390	1578
HH	6.523	-2.315	157.971	190.998	4.410	2041	8.355	7251
PP	6.698	-2.456	169.566	197.361	3.921	2325	9.998	1967

TABLE VII (CONTINUED)

REGRESSION MODEL RESULTS

FILTERED DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
B	2.248	.998	13.346	69.418*	3.393	1408	1.181*	1566
D	2.103	.475	10.679	78.754	3.058	1246	1.396	1728
F	2.292	.733	12.175	80.338	2.526	1791	1.943	1183
K	2.463	-0.094	10.853	104.900	4.143	790	1.650	2184
L	2.134	.420	10.806	79.266	3.107	1211	1.439	1763
N	2.155	.477	10.691	79.668	2.725	1435	1.609	1539
BB	2.072*	.141*	9.625	83.436	2.659	1214	1.623	1760
DD	2.111	-0.257	9.206	93.601	2.497	1101	1.874	1873
FF	2.295	-0.237	10.052	98.910	1.831*	1688	2.905	1286
GG	2.078	.182	9.191*	85.402	2.009	1668	2.139	1306
HH	2.117	-0.322	9.193	93.548	2.455	1078	1.902	1896
PP	2.152	-0.338	9.334	94.833	2.042	1322	2.227	1652

in each case. For model B, the forecast is a function of just the recurring demand forecast which is exponentially determined. Model B, therefore, is the model that best fits using all the data.

When the regression models were run with the filtered data there was no clear cut "best" model. Model BB did, however, show well in the two categories of MAE and MFE. Model BB also had a RMSFE that was close to the lowest values obtained. Model BB appears to provide the best fit when only filtered data are used.

The results are interesting in that model B was obtained through regressions on raw data and then tested the best using the MOE's. Model BB is the same model as B, except that it was obtained through regressions on filtered data on which it subsequently tested as the best model. Both models identified carcass return forecasts as a function of the recurring demand forecasts. Model BB (determined by the filtered data) did a relatively good job of forecasting when all the data was tested, but conversely model B did not show particularly well against the filtered data except with respect to the MAPE measure. It is important to note that all models did significantly better jobs of forecasting when the data was first filtered before being applied to the models.

B. EXPONENTIAL SMOOTHING (ES)

The results of the pure exponential smoothing model are displayed in Tables 8 and 9 for raw and filtered data respectively. Unlike the UICP exponential smoothing model, these models did not have a filtering or screening system.

For the models synthesized with all the SPCC data, Table 8 shows that, except for MFE, [.35, .50] is the optimal range for α. This is greater weight than those used by the UICP models [0.1, 0.3]. Again, it is important to note that no filtering is used in this model as in the actual UICP models. The MFE calculation is highest at $\alpha = .05$ and is monotonically decreasing to its low value at the boundary value of $\alpha = 1.0$ (or the naive forecasting model). The model that will be compared with other models will be $\alpha = .4$ because it is in the above optimal range.

Table 9 displays the results when the exponential smoothing models are applied to data that has already been filtered. Here, the model with $\alpha = .2$ appears to be the best, even though there is little difference between it and the model with $\alpha = .25$. Of interest is that MFE is not monotonically increasing as with the raw data, but the RMSFE is.

For the exponential smoothing models there is a difference between the MOE's as a result of using different input data, but not as significant as with the reqression

TABLE VIII

EXPONENTIAL SMOOTHING MODEL RESULTS

RAW DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
α = .05	2.992	.829	16.783	70.739	3.223	2534	2.636	1768
.10	2.907	.831	16.198	69.210	3.158	2531	2.524	1761
.15	2.841	.830	15.728	68.111	3.097	2533	2.446	1759
.20	2.793	.826	15.345	67.396	3.063	2528	2.386	1764
.25	2.760	.820	15.053	66.962	3.013	2544	2.376	1748
.30	2.737	.811	14.834	66.774	2.996	2535	2.347	1757
.35	2.722	.800	14.679	66.769*	2.986	2529	2.334*	1763
.40	2.715*	.787	14.593	66.903	2.964	2538	2.352	1754
.45	2.717	.774	14.526	67.194	2.960	2531	2.361	1761
.50	2.729	.759	14.516*	67.579	2.941*	2548	2.415	1744
.55	2.745	.743	14.542	68.085	2.952	2539	2.443	1753
.60	2.767	.728	14.602	68.644	2.954	2541	2.493	1751
.65	2.794	.712	14.690	69.255	2.963	2542	2.545	1750

TABLE VIII (CONTINUED)

EXPONENTIAL SMOOTHING MODEL RESULTS

RAW DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
α = .70	2.828	.696	14.807	69.923	2.974	2547	2.613	1745
.75	2.866	.680	14.947	70.643	2.993	2549	2.681	1743
.80	2.906	.664	15.110	71.393	3.006	2554	2.757	1738
.85	2.950	.649	15.293	72.184	3.024	2559	2.840	1733
.90	2.997	.635	15.496	73.011	3.044	2565	2.924	1727
.95	3.044	.621	15.718	73.856	3.072	2565	3.001	1727
1.00	3.097	.607*	15.958	74.713	2.476	3218	4.955	[illegible]4

TABLE IX

EXPONENTIAL SMOOTHING MODEL RESULTS

FILTERED DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
α = .05	1.953	.390	8.934*	67.914	2.180	1593	1.676	1381
.10	1.926	.399	8.964	66.914	2.165	1592	1.635	1382
.15	1.910	.407	9.029	66.289	2.148	1597	1.614	1377
.20	1.903*	.418	9.121	66.027	2.153	1593	1.598*	1381
.25	1.904	.414	9.236	66.022*	2.140	1606	1.611	1368
.30	1.910	.414	9.367	66.244	2.159	1596	1.606	1378
.35	1.922	.413	9.513	66.612	2.182	1589	1.610	1385
.40	1.937	.410	9.671	67.073	2.189	1595	1.637	1379
.45	1.956	.407	9.840	67.656	2.213	1586	1.648	1388
.50	1.979	.393	10.018	68.290	2.220	1595	1.689	1379
.55	2.007	.397	10.203	69.008	2.249	1587	1.713	1387
.60	2.033	.391	10.394	69.752	2.266	1589	1.751	1385
.65	2.063	.385	10.591	70.519	2.290	1588	1.787	1386

TABLE IX (CONTINUED)

EXPONENTIAL SMOOTHING MODEL RESULTS

FILTERED DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
α = .70	2.095	.379	10.791	71.298	2.312	1591	1.830	1383
.75	2.128	.372	10.996	72.089	2.336	1591	1.872	1383
.80	2.161	.366	11.202	72.871	2.357	1594	1.919	1380
.85	2.197	.360	11.411	73.665	2.383	1596	1.965	1378
.90	2.234	.355	11.621	74.464	2.407	1598	2.013	1376
.95	2.270	.350	11.847	75.241	2.436	1598	2.057	1376
1.00	2.308	.345*	12.049	76.021	1.829*	2153	3.516	821

models. This probably results from the exponential smoothing models being more "flexible" or robust with respect to data with large variances as compared to the fixed parameter regression models. The model with $\alpha = 1.0$ which predicts carcass returns as merely what they actually were in the last period did a better forecasting job than the respective regression models F and FF where carcass returns were a fixed percentage of recurring demands from the previous quarter.

C. MOVING LEAST SQUARES (MLS)

The moving least squares model results are listed in Table 10. The left-hand column indicates "MLS" for moving least squares and the number of quarters used in each model for determining the forecast. In the case of both input data, the model predicated on the previous four quarters did the best. As explained previously, the model was limited to reaching back four quarters to obtain a base for making the forecast, and therefore, it cannot be determined if five or more quarters would have made better models. The four quarter model does tend to smooth out outliers more than the two quarters models. While the models using filtered data did show slightly improved MOE statistics, the MAPE for both data sets was virtually identical indicating that the model is very robust and equally good (or bad) with raw or filtered data.

TABLE X

MOVING AVERAGE MODEL RESULTS

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
RAW DATA								
MLS - 2QTR	5.029	.322*	24.272	143.125	4.034	3165	7.416	1127
3QTR	4.030	.480	20.947	110.533	3.276	2958	5.649	1334
4QTR	3.592*	.571	18.495*	96.939*	3.001*	2975	4.867*	1317
FILTERED DATA								
MLS - 2QTR	3.853	.293*	18.774	144.286	2.926	2097	5.942	877
3QTR	2.976	.296	16.276	111.241	2.525	1919	3.715	1055
4QTR	2.692*	.312	14.561*	96.959*	2.290*	1940	3.378*	1034
RAW DATA								
MA - 2QTR	2.813	.750*	15.120	70.032	2.615*	2923	3.213	1369
3QTR	2.766	.814	14.691	67.789	2.769	2758	2.713	1534
4QTR	2.737*	.852	14.685*	66.442*	2.867	2662	2.473*	1630

TABLE X (CONTINUED)

MOVING AVERAGE MODEL RESULTS

FILTERED DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
MA - 2QTR	2.065	.372*	11.024	72.114	1.889*	1910	2.338	1064
3QTR	2.009	.396	10.024	69.136	1.995	1778	1.984	1196
4QTR	1.912*	.413	8.911*	66.345*	2.011	1700	1.739*	1274

D. MOVING AVERAGE (MA)

The moving average model results are also listed in Table 10 just below the moving least square results and identified as "MA" models. While the two quarter models showed some promise, the four quarter models again were overall better. The four quarter models tend to smooth outliers into the forecast more effectively than shorter quarter input models. Again, as in the MLS model, the results did not vary drastically for the raw and filtered data indicating that the moving average model is also fairly robust.

E. ALL MODELS

Table 11 lists all the models developed and discussed in the models section. It only includes one candidate variation of each of the models discussed previously in this chapter. The models are:

SPCC - UICP exponential smoothing model in use at SPCC,

ARR - adaptive response rate model,

DEMAND - SPCC proposed demand/return model,

LAG - time-lag carcass return model,

REG-ADV - advice code regression model,

REG-B - recurring demand regression model B,

REG-BB - recurring demand regression model BB,

MLS-4 QTR - moving least square 4 quarter model,

TABLE XI

COMPARISON OF RESULTS OF ALL MODELS

RAW DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
SPCC	2.767	.902	15.379	63.954*	2.889	2711	2.524	1581
ARR	3.074	.210*	15.011	85.882	2.783*	2543	3.508	1749
DEMAND	7.654	1.404	70.825	165.820	7.936	2454	7.330	1836
LAG	6.192	-2.268	136.021	174.206	4.312	1946	7.652	2346
REG-ADV	4.210	1.912	27.002	90.248	4.947	2679	2.921	1613
REG - B	5.065	.383	77.225	116.211	4.816	2411	5.281	1881
MLS - 4QTR	3.592	.571	18.495	96.939	3.001	2975	4.867	1317
MA - 4QTR	2.737	.852	14.685	66.442	2.867	2662	2.473	1630
ES - α = .04	2.715*	.787	14.593*	66.903	2.964	2538	2.352*	1754

TABLE XI (CONTINUED)

COMPARISON OF RESULTS OF ALL MODELS

FILTERED DATA

MODEL	MAE	MFE	RMSFE	MAPE	MPE	NO.	MNE	NO.
SPCC	1.898*	.478	9.299	64.068*	2.009*	1748	1.709	1226
ARR	2.262	.044*	10.304	83.941	2.148	1590	2.360	1384
DEMAND	6.095	1.264	70.017	132.193	7.647	1446	4.745	1528
LAG	2.099	-.557	8.967	96.456	2.272	1001	1.995	1973
REG-ADV	3.266	.676	21.619	98.339	3.583	1627	2.718	1347
REG-BB	2.072	.141	9.625	83.436	2.659	1214	1.623	1760
MLS - 4QTR	2.692	.312	14.561	96.959	2.290	1940	3.378	1034
MA - 4QTR	1.912	.413	8.911*	66.345	2.011	1700	1.739	1274
ES - α = .2	1.903	.418	9.121	66.027	2.153	1593	1.598*	1381

MA-4 QTR - moving average four quarter model,

ES-α=.4 - exponential smoothing model with α = .4, and

ES-α=.2 - exponential smoothing model with α = .2.

Using both types of data, the DEMAND model had the worst showing overall. Measured against the raw data, three techniques were approximately equal in their demonstrated forecasting abilities - the SPCC model, ARR and ES-α=.4. The SPCC model was the only one of the three to employ a filter. The three models are similar in that they all basically employ the exponential smoothing technique to produce the forecast. The moving average and the moving least squares models were next in forecasting abilities, with the moving average model clearly superior to the moving least squares model. This could be explained by the fact that the MA model is simply the average of the previous four observations, thus smoothing out extraneous data points while the MLS is a projection of a "best fit" line through the data points. The implication is that the carcass returns follow an average value pattern more than a demonstrated trend. The remaining models are all causal or regression type schemes with fixed parameters. As a group, they did not forecast with the same accuracy as the other models. The advice code regression model displayed the most potential as an estimator of carcass returns.

The current SPCC forecasting model makes the overall best forecasts when synthesized with the filtered data. Even though the RMSFE for the MA-4 QTR model is lower, the SPCC model does almost as well. The ARR model did as well as with the raw data, but the exponential smoothing model ES-α=.2 (no filters in the model as in the SPCC model) did almost as well or better than the SPCC model for all MOE categories. This is probably explained by the fact that the SPCC model α value, which is either .1 or .3 depending on the trending present, brackets the ES model with α=.2. The high filter in the SPCC model is probably not necessary because of the filtering previously performed on the data. This would bring almost all of the observations to within six standard deviations of the average carcass return rate, thus virtually eliminating the high filter gross adjustments. Again the moving average model shows better MOE performance than the moving least squares model. The filtered causal models all show significant improvement in their forecasting abilities over their unfiltered counterparts except for the SPCC proposed DEMAND model which shows only slight improvement despite the filtering process. The model REG-BB which was determined through regressions on the filtered data does the best of the causal models. However, as discussed earlier there is probably some bias involved in using the same set of data to both derive the model and then test it. The significance of the regression model is that it may help to identify the carcass return pattern of a "normal" recurring demand situation. This results from eliminating the outliers before modeling.

The models as a whole were able to forecast significantly better as measured by the MOE's when a filtering process was applied to the data before synthesizing with the models.

IX. CONCLUSION

The following discussion will contain qualifications to the study, conclusions of the study and areas for further consideration.

A. QUALIFICATIONS

There are several qualifications to this forecasting study.

1) The data used to build the forecasting models and to test the models was not a random sampling from all SPCC managed repairable items. The data selection process was constructed with the intent of identifying items that had an established observable pattern of recurring demand. Also the data were restricted to those recurring demands and carcass returns specifically identified to a particular item (e.g. no family items).

2) The short time frame for which data were available by quarters from the IHF precluded the use of may time-series dependent models. This situation may also have contributed to the poor performance of the SPCC proposed DEMAND model because there may not have been a long enough start up or baseline period to establish long term (or steady state) repair survival rates and wearout rates.

3) The lack of cumulative data totals and forecasts for all data items at the beginning of the study required that half of the data available for each item be used to either build the model to be tested or used as start up data for the forecasting techniques to be employed over the final four quarters actual data. The start up period necessarily limited the scope of the parameters of some of the forecasting models - specifically moving average and moving least squares.

4) The timing of the forecasting study may have been bad because of the initiation of the Navy Stock Fund - Depot Level Repairables Test funding change that

occurred 1 April 1981. Thus five quarters of the data used in the study was pre-NSF funding of repairables and the other three quarters data was generated under stock funding. The purpose of the funding change was to alter the pattern of repairable demands and carcass returns.

5) There was no attempt to address the qualities of the UICP recurring demand forecasting scheme.

B. CONCLUSIONS

From the study, the following general conclusions can be rendered.

1) Filtering the data prior to applying any forecasting technique is critical. This point was illustrated for all the forecasting models when a gross filter was applied across the board against all data. The current UICP model which SPCC uses already employs a filter which was apparent in the results.

2) The autoregressive models were superior to the causal models. Despite the cause and effect relationship of recurring demands to carcass returns, the methods that attempted to model this relationship did not forecast carcass returns as well as the models predicated upon previous carcass return patterns. This may tend to indicate that the two events follow separate underlying distribution patterns.

3) The exponential smoothing models were the best of the autoregressive models. The SPCC model, the adaptive response rate model and the pure exponential smoothing models all work on the same basic principle. For use with raw data, the straight exponential smoothing model with $\alpha = .4$ (no filtering) does as well or better a job of forecasting as does the current UICP model.

4) The carcass return - recurring demand relationship could not be definitely established through regression analysis. Without filtering, all the models demonstrated R^2 statistics of approximately .5 with standard deviations of approximately 20. The regression models determined from the filtered data showed significant improvement in both statistics, but still exhibited large standard deviations of around 10.

5) The best forecasts made by the models were not very good from a relative standpoint. The best mean absolute percentage error was 64 percent. This results in a very wide confidence band around an estimate and does not eliminate the uncertainty surrounding the long procurement lead times that the forecasting models are used for. This is a result of one or both of the following:

   a) the true underlying distribution of carcass returns is still not properly identified, or

   b) there are other factors causing wide data fluctuations.

These factors could include policies, funding, reporting procedures and/or handling procedures. These factors obviously affect the recurring demand and carcass return patterns.

C. AREAS FOR FURTHER STUDY

The following areas should be considered for further study:

1) outlier analysis techniques - how to properly identify and screen outliers from the data base,

2) time-series analysis of carcass return forecasting - this will require an accumulation of quarterly data over a longer time period,

3) forecast carcass returns as a function of fleet item population - this method would utilize the Weapons System Files at SPCC as the basis for forecasting,

4) regressions based upon four digit ICP COG designations, and

5) the effects of the NSF-DLR test on carcass return rates - regressions on data to determine before and after carcass return rates as functions of recurring demand.

The material in this thesis could serve as a baseline for developing the above topic areas.

APPENDIX A

MOVING LEAST SQUARES EXAMPLE

QUARTER	1	2	3	4	5	6	7	8
ACTUAL CARCASS RETURNS	5	6	2	4	7	8	8	9

n = 4

t = n + 1 = 4 + 1 = 5

First Input Qtrs 1-4

X coordinates 1-4, Y = 5, 6, 2, 4

Regression Line f(X) = -.7X + 6

X = 5

Forecast for Qtr 5 = f(5) = -.7(5) + 6 = 2.5   Actual 7

Second Input Qtrs 2-5

X coordinates 1-4, Y = 6, 2, 4, 7

Regression Line f(X) = .5X + 3.5

X = 5

Forecast for Qtr 6 = f(5) = .5(5) + 3.5 = 6   Actual 8

Third Input Qtrs 3-6

X coordinates 1-4, Y = 2, 4, 7, 8

Regression Line f(X) = 2.1X + 0

X = 5

Forecast for Qtr 7 = f(5) = 2.1(5) = 10.5   Actual 8

Fourth Input Qtrs 4-7

X coordinates 1-4, Y = 4, 7, 8, 8

Regression Line $f(X) = 1.3X + 3.5$

$X = 5$

Forecast for Qtr 8 = $f(5) = 1.3(5) + 3.5 = 10$ Actual 9

APPENDIX B

THF DATA COLLECTION PARAMETERS

The following breakdown is the coding that was used to collect data from the SPCC THF file for each listed data category:

DATA CATEGORY	D.I.	CC1	CC2	NOTE
Inductions into repair	DAC	*	M	
	D8C	*	M	
Collection Point Surveys	DAC	F	H	1
	D7C	F	H	1
DOP surveys	DAC	M	H	
	D8C	*	H	
Assets to "A" condition	DAC	M	A	
	D8C	*	A	
Demands by advice codes	A0-	-	-	2
	A4-	-	-	2
	D7-	-	-	2

NOTES:

1. any unit identification code as part of the requisition number but N00104 (indicating SPCC directed survey)

2. the three document identifiers all represent recurring demand requisitions which were further broken down into recurring demands per quarter by specific advice codes

* any condition code

D.I. document identifier, see [Ref. 3]

CC- conditions code, see [Ref. 3]

APPENDIX C

RANDOM SAMPLING PLAN

The following random sampling scheme was suggested by Dr. P. A. W. Lewis, Professor of Operations Research and Statistics, Naval Postgraduate School, Monterey, Ca.

The objective is to obtain a 10 percent sample (or 430 items) out of a population of 4292 NIIN's without repeating any items. The methodology was to establish a vector, call it L(I), with 4292 cells and an index register where I = 1,2,...,4292. Initialize the value in each cell to correspond to the cell or index number (i.e. cell 1 or L(1) contains 1, L(2) contains 2, etc.). Next draw a pseudo random number (call it R(1)) from the uniform [0,1] distribution using the IBM IMSL library program GGUBS. Multiply R(1) by Imax (the maximum value in the index register - 4292 at this point) and integerize to obtain a cell number (call it N) from 1 to 4292. Then go to vector location L(N) and the number in the cell is the first number for the sample. Replace the number in location L(N) by the number in L(Imax) (which is still 4292 in this case) and decrement the location index I by one (now I = 1,2,...,4291). Repeat the operation 430 times. The result is a vector of 430 non-duplicate numbers ranging from 1 to 4292.

The master NIIN file is a listing of all 4292 NIIN's in numerically ascending order. The vector represents the relative position of the NIIN's within the master list (i.e. number 2 in the vector corresponds to the second NIIN in the master NIIN list). Then using a locally generated utility program, this vector is applied to the master NIIN file and the 430 appropriate NIIN's are extracted. The 430 NIIN's represent the random sample.

APPENDIX D

SYNTHESIS RESULTS BY QUARTER

MOE: MEAN ABSOLUTE ERROR

RAW DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
B	5.288	5.002	4.858	5.110	5.065
D	8.891	4.265	4.260	4.708	5.531
F	11.268	3.598	3.767	4.492	5.781
K	6.521	6.565	7.191	4.711	6.247
L	6.251	6.371	7.009	4.539	6.043
N	8.654	7.468	3.792	4.363	6.069
BB	6.030	5.335	5.095	5.203	5.416
DD	11.152	4.189	4.309	4.715	6.091
FF	13.758	3.606	3.939	4.575	6.470
GG	9.687	8.068	4.189	4.510	6.589
HH	9.544	7.968	4.114	4.465	6.523
PP	10.077	8.381	3.963	4.369	6.698

MOE: MEAN ABSOLUTE ERROR

FILTERED DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
B	1.827	2.230	2.089	2.847	2.248
D	1.840	1.993	1.908	2.670	2.103
F	2.014	2.200	2.090	2.865	2.292
K	2.158	2.278	2.163	2.749	2.463
L	1.874	2.083	1.980	2.598	2.134
N	1.910	2.108	1.965	2.636	2.155
BB	1.841	1.956	1.887	2.603	2.072
DD	1.924	1.857	1.987	2.676	2.111
FF	2.081	1.999	2.211	2.890	2.295
GG	1.937	1.896	1.993	2.485	2.078
HH	2.007	1.897	2.019	2.543	2.117
PP	2.040	1.930	2.072	2.565	2.152

MOE: MEAN FORECAST ERROR

RAW DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
B	-1.552	.074	.964	2.044	.383
D	-5.451	.248	.943	1.720	-0.641
F	-7.297	1.399	1.835	2.325	-0.435
K	-3.491	-2.482	-2.213	1.489	-1.674
L	-2.990	-1.980	-1.710	2.002	-1.170
N	-5.279	-2.763	1.523	2.177	-1.086
BB	-3.075	-1.236	-.208	.942	-0.894
DD	-8.226	-.384	.289	.954	-1.842
FF	-10.538	.419	.867	1.258	-1.999
GG	-6.338	-3.640	1.004	1.697	-1.819
HH	-6.826	-4.131	.503	1.196	-2.315
PP	-7.335	-4.496	.697	1.311	-2.456

MOE: MEAN FORECAST ERROR

FILTERED DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
B	.233	1.200	.992	1.568	.998
D	-.107	.757	.442	.806	.475
F	.295	1.066	.671	.899	.733
K	-.832	.063	-.025	.417	-0.094
L	-.317	.577	.490	.930	.420
N	-.234	.858	.479	.803	.477
BB	-.627	.357	.146	.686	.141
DD	-.749	.074	-.296	-.057	-0.257
FF	-.582	.151	-.303	-.212	-0.237
GG	-.531	.587	.196	.474	.182
HH	-1.035	.083	-.308	-.029	-0.322
PP	-1.041	.096	-.323	-.085	-0.338

MOE: ROOT MEAN SQUARE FORECAST ERROR

RAW DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
B	116.672	84.087	60.855	47.286	77.225
D	326.396	50.781	38.323	33.824	112.331
F	467.155	25.449	22.013	27.088	135.426
K	161.572	143.774	185.816	27.549	129.678
L	162.173	144.337	186.413	27.584	130.127
N	281.810	231.777	22.796	26.104	140.622
BB	148.360	105.468	75.435	56.062	96.331
DD	449.225	46.454	35.462	31.908	140.762
FF	601.678	26.696	22.371	26.368	169.278
GG	318.476	262.377	25.943	26.630	158.357
HH	317.731	261.705	25.866	26.581	157.971
PP	343.566	285.193	23.793	25.713	169.566

MOE: ROOT MEAN SQUARE FORECAST ERROR

FILTERED DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
B	9.607	15.866	10.890	17.022	13.346
D	8.452	11.613	7.388	15.263	10.679
F	10.521	12.672	8.300	17.205	12.175
K	8.857	12.657	8.008	13.890	10.853
L	8.797	12.593	7.965	13.868	10.806
N	9.009	12.282	7.453	14.021	10.691
BB	7.329	10.560	7.085	13.547	9.625
DD	7.744	7.659	7.247	14.173	9.206
FF	8.439	7.864	8.294	15.607	10.052
GG	8.783	7.721	7.753	12.506	9.191
HH	8.802	7.760	7.712	12.499	9.193
PP	9.037	7.720	8.039	12.538	9.334

MOE: MEAN ABSOLUTE PERCENTAGE ERROR

RAW DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
B	132.047	139.507	101.334	91.957	116.211
D	211.703	121.140	101.637	100.071	133.638
F	251.963	86.395	89.020	95.557	130.734
K	193.856	225.533	191.918	117.345	182.163
L	162.681	199.533	165.782	92.850	155.212
N	203.408	265.883	92.710	91.977	163.495
BB	165.578	172.348	123.473	111.230	143.157
DD	271.111	131.761	116.011	117.469	159.091
FF	321.007	105.002	109.239	118.551	163.450
GG	237.959	308.180	113.291	108.894	192.081
HH	237.397	304.072	112.257	110.267	190.998
PP	247.285	323.126	109.662	109.371	197.361

MOE: MEAN ABSOLUTE PERCENTAGE ERROR

FILTERED DATA

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
B	73.182	61.997	64.366	78.128	69.418
D	81.319	66.743	72.544	94.408	78.754
F	78.945	67.574	74.772	100.062	80.338
K	115.240	95.351	98.569	110.441	104.900
L	84.859	70.417	73.549	88.237	79.266
N	83.258	68.499	74.587	92.327	79.668
BB	90.898	73.351	76.303	93.192	83.436
DD	96.943	77.460	85.793	114.209	93.601
FF	98.883	80.765	91.366	124.627	98.910
GG	92.119	74.499	77.948	97.041	85.402
HH	100.538	79.340	86.203	108.109	93.548
PP	101.327	80.200	87.756	110.048	94.833

MOE: MEAN ERROR (RAW DATA AND FILTERED DATA)

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR7 ERROR	QTR7 OBS	QTR 8 ERROR	QTR 8 OBS	$\bar{X}$	AVE. NO.
MOE:	MEAN ERROR (RAW DATA)										
B	Pos	3.625	2212	4.369	2493	5.098	2451	6.171	2488	4.816	2411
	Neg	7.057	2080	5.879	1799	4.540	1841	3.646	1804	5.281	1881
D	Pos	3.521	2097	4.173	2321	4.919	2270	6.159	2240	4.693	2232
	Neg	14.022	2195	4.374	1971	3.521	2022	3.124	2052	6.260	2060
F	Pos	[illegible].016	2826	3.565	3009	4.155	2894	5.381	2719	4.029	2862
	Neg	27.178	1466	3.678	1283	2.967	1398	2.958	1573	9.195	1430
K	Pos	7.688	8f6	7.575	1157	8.881	1203	10.430	1276	8.644	1121
	Neg	6.235	3446	6.193	3135	6.533	3089	2.293	3016	5.314	3171
L	Pos	3.443	2033	4.163	2264	5.096	2232	6.292	2231	4.749	2190
	Neg	8.779	2259	8.837	2028	9.084	2060	2.642	2061	7.336	2102
N	Pos	3.120	2321	3.884	2600	4.533	2517	5.893	2382	4.358	2455
	Neg	15.170	1971	12.978	1692	2.744	1775	2.456	1910	8.337	1837
BB	Pos	3.259	1946	3.882	2266	4.662	2250	5.779	2282	4.396	2186
	Neg	8.328	2346	6.961	2026	5.573	2042	4.550	2010	6.353	2106
DD	Pos	3.199	1963	3.792	2154	4.710	2095	5.947	2046	4.412	2065
	Neg	17.855	2329	4.591	2138	3.926	2197	3.594	2246	7.492	2227
FF	Pos	2.549	2711	2.985	2894	3.726	2769	4.848	2582	3.527	2739
	Neg	32.979	1581	4.894	1398	4.329	1523	4.163	1710	11.591	1553

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\overline{X}$	AVE. NO.
MOE:	MEAN ERROR (RAW DATA) (CONTINUED)										
GG	Pos	2.696	2586	3.341	2844	4.034	2763	5.004	2662	3.769	2714
	Neg	20.034	1706	17.352	1448	4.471	1529	3.704	1630	11.390	1578
HH	Pos	3.071	1899	3.826	2152	4.783	2072	5.959	2039	4.410	2041
	Neg	14.680	2393	12.133	2140	3.491	2220	3.115	2253	8.355	2251
PP	Pos	2.666	2207	3.369	2475	4.206	2378	5.443	2240	3.921	2325
	Neg	17.923	2085	15.209	1817	3.662	1914	3.198	2052	9.998	1967
MOE:	MEAN ERROR (FILTERED DATA)										
B	Pos	2.450	1251	3.440	1483	3.211	1427	4.470	1469	3.393	1408
	Neg	1.376	1723	1.028	1491	1.055	1547	1.264	1505	1.181	1566
D	Pos	2.260	1140	3.077	1329	2.765	1264	4.130	1252	3.058	1246
	Neg	1.579	1834	1.118	1645	1.275	1710	1.610	1722	1.396	1728
F	Pos	1.938	1772	2.530	1920	2.271	1808	3.363	1664	2.526	1791
	Neg	2.127	1202	1.600	1054	1.811	1166	2.232	1310	1.943	1183
K	Pos	3.467	569	4.267	816	3.763	845	5.074	928	4.143	790
	Neg	1.848	2405	1.527	2158	1.528	2129	1.696	2046	1.650	2184
L	Pos	2.119	1093	3.099	1277	2.991	1228	4.219	1244	3.107	1211
	Neg	1.733	1881	1.320	1697	1.269	1746	1.434	1730	1.439	1763
N	Pos	1.861	1340	2.833	1557	2.466	1474	3.739	1368	2.725	1435
	Neg	1.952	1634	1.312	1417	1.473	1500	1.698	1606	1.609	1539

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\bar{X}$	AVE. NO.
MOE: MEAN ERROR (FILTERED DATA) (CONTINUED)											
BB	Pos	1.758	1027	2.682	1283	2.411	1254	3.783	1293	2.659	1214
	Neg	1.885	1947	1.406	1691	1.506	1720	1.696	1681	1.623	1760
DD	Pos	1.699	1028	2.432	1181	2.261	1112	3.597	1083	2.497	1101
	Neg	2.043	1946	1.479	1793	1.824	1862	2.149	1891	1.874	1873
FF	Pos	1.331	1675	1.752	1825	1.665	1705	2.574	1548	1.831	1688
	Neg	3.049	1299	2.391	1149	2.946	1269	3.235	1426	2.905	1286
GG	Pos	1.330	1572	2.070	1784	1.920	1696	2.715	1621	2.009	1668
	Neg	2.618	1402	1.635	1190	2.091	1278	2.212	1353	2.139	1306
HH	Pos	1.482	976	2.500	1178	2.342	1087	3.495	1070	2.455	1078
	Neg	2.264	1998	1.502	1796	1.834	1887	2.009	1904	1.902	1896
PP	Pos	1.198	1241	2.072	1454	1.930	1348	2.968	1243	2.042	1322
	Neg	2.644	1733	1.794	1520	2.191	1626	2.277	1731	2.227	1652

MOE: MEAN ABSOLUTE ERROR (RAW DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	2.345	2.644	3.126	3.853	2.992
.10	2.311	2.584	3.011	3.722	2.907
.15	2.280	2.539	2.922	3.621	2.841
.20	2.252	2.503	2.852	3.565	2.793
.25	2.229	2.473	2.796	3.541	2.760
.30	2.209	2.450	2.749	3.539	2.737
.35	2.191	2.439	2.710	3.549	2.722
.40	2.176	2.439	2.681	3.565	2.715
.45	2.164	2.449	2.662	3.593	2.717
.50	2.162	2.475	2.649	3.628	2.729
.55	2.167	2.507	2.643	3.664	2.745
.60	2.177	2.540	2.652	3.700	2.767
.65	2.197	2.575	2.666	3.736	2.794
.70	2.227	2.613	2.686	3.784	2.828
.75	2.259	2.659	2.710	3.834	2.866

MOE: MEAN ABSOLUTE ERROR (RAW DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
α = .80	2.293	2.705	2.742	3.882	2.906
.85	2.335	2.751	2.782	3.932	2.950
.90	2.380	2.798	2.825	3.983	2.997
.95	2.427	2.846	2.871	4.033	3.044
1.00	2.475	2.898	2.930	4.085	3.097

MOE: MEAN FORECAST ERROR (RAW DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	-.195	.672	1.027	1.811	.829
.10	-.167	.707	1.026	1.758	.831
.15	-.138	.740	1.018	1.700	.830
.20	-.109	.770	1.005	1.639	.826
.25	-.081	.797	.987	1.575	.820
.30	-.052	.821	.964	1.509	.811
.35	-.024	.842	.936	1.444	.800
.40	.005	.860	.905	1.378	.787
.45	.033	.876	.871	1.314	.774
.50	.062	.888	.833	1.252	.759
.55	.091	.898	.793	1.190	.743
.60	.119	.905	.751	1.135	.728
.65	.148	.909	.707	1.083	.712
.70	.176	.910	.662	1.034	.696
.75	.205	.909	.616	.989	.680

MOE: MEAN FORECAST ERROR (RAW DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .80	.234	.904	.570	.949	.664
.85	.262	.897	.524	.914	.649
.90	.291	.886	.478	.883	.635
.95	.319	.873	.433	.857	.621
1.00	.348	.857	.389	.835	.607

MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	11.782	16.774	18.488	20.088	16.783
.10	11.487	16.575	17.573	19.155	16.198
.15	11.218	16.434	16.773	18.485	15.728
.20	10.978	16.343	16.080	17.978	15.345
.25	10.769	16.296	15.487	17.659	15.053
.30	10.592	16.284	14.984	17.475	14.834
.35	10.450	16.301	14.566	17.398	14.679
.40	10.343	16.341	14.228	17.401	14.593
.45	10.273	16.498	13.966	17.467	14.526
.50	10.241	16.467	13.777	17.578	14.516
.55	10.246	16.544	13.659	17.720	14.542
.60	10.290	16.625	13.608	17.884	14.602
.65	10.370	16.704	13.623	18.062	14.690
.70	10.487	16.792	13.701	18.248	14.807
.75	10.640	16.874	13.837	18.438	14.947

MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
α = .80	10.826	16.954	14.030	18.629	15.110
.85	11.044	17.034	14.274	18.820	15.293
.90	11.293	17.113	14.565	19.013	15.496
.95	11.570	17.193	14.899	19.208	15.718
1.00	11.873	17.278	15.270	19.411	15.958

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	71.510	65.806	67.945	77.694	70.739
.10	70.352	64.271	65.537	76.681	69.210
.15	69.297	63.040	63.731	76.375	68.111
.20	68.327	62.105	62.463	76.689	67.396
.25	67.405	61.394	61.605	77.444	66.962
.30	66.633	60.863	61.066	78.535	66.774
.35	65.895	60.511	60.799	79.870	66.769
.40	65.208	60.327	60.745	81.333	66.903
.45	64.724	60.308	60.893	82.849	67.194
.50	64.272	60.440	61.239	84.366	67.579
.55	63.998	60.741	61.720	85.879	68.085
.60	63.794	61.127	62.302	87.352	68.644
.65	63.651	61.627	62.974	88.768	69.255
.70	63.570	62.234	63.779	90.107	69.923
.75	63.561	62.949	64.668	91.394	70.643

MOE: MEAN ABSOULTE PERCENTAGE ERROR (RAW DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .80	63.609	63.727	65.619	92.616	71.393
.85	63.745	64.609	66.595	93.788	72.184
.90	63.945	65.588	67.697	94.914	73.011
.95	64.161	66.633	68.638	95.992	73.856
1.00	64.436	67.648	69.731	97.038	74.713

MOE: MEAN ERROR (RAW DATA) MODEL: ES

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\overline{X}$	AVE. NO.
α = .05	Pos	1.902	2426	2.709	2627	3.526	2528	4.756	2556	3.223	2534
	Neg	2.922	1866	2.542	1665	2.553	1764	2.525	1736	2.636	1758
α = .10	Pos	1.902	2420	2.685	2631	3.434	2523	4.612	2550	3.158	2531
	Neg	2.840	1872	2.425	1661	2.410	1769	2.420	1742	2.524	1761
α = .15	Pos	1.903	2415	2.676	2630	3.346	2527	4.463	2559	3.097	2533
	Neg	2.764	1877	2.324	1662	2.316	1765	2.379	1733	2.446	1759
α = .20	Pos	1.901	2420	2.674	2627	3.281	2523	4.397	2540	3.063	2528
	Neg	2.708	1872	2.235	1665	2.241	1769	2.360	1752	2.386	1764
α = .25	Pos	1.885	2446	2.641	2657	3.210	2529	4.315	2545	3.013	2544
	Neg	2.686	1846	2.201	1635	2.203	1763	2.415	1747	2.376	1748
α = .30	Pos	1.909	2425	2.640	2659	3.158	2523	4.276	2534	2.996	2535
	Neg	2.600	1867	2.142	1633	2.167	1769	2.478	1758	2.347	1757
α = .35	Pos	1.916	2428	2.643	2664	3.112	2515	4.271	2509	2.986	2529
	Neg	2.551	1864	2.106	1628	2.143	1777	2.535	1783	2.334	1763
α = .40	Pos	1.902	2461	2.642	2680	3.064	2512	4.248	2498	2.964	2538
	Neg	2.545	1831	2.103	1612	2.142	1780	2.617	1794	2.352	1754
α = .45	Pos	1.932	2441	2.663	2679	3.022	2509	4.223	2494	2.960	2531
	Neg	2.470	1851	2.094	1613	2.157	1783	2.721	1798	2.361	1761
α = .50	Pos	1.924	2481	2.670	2703	2.980	2508	4.191	2499	2.941	2548
	Neg	2.489	1811	2.143	1589	2.185	1784	2.844	1793	2.415	1744

MOE: MEAN ERROR (RAW DATA) (CONTINUED) MODEL: ES

MODEL		QTR 5		QTR 6		QTR 7		QTR 8			
		ERROR	OBS	ERROR	OBS	ERROR	OBS	ERROR	OBS	$\bar{X}$	AVE. NO.
α = .55	Pos	1.962	2470	2.719	2690	2.950	2500	4.177	2495	2.952	2539
	Neg	2.447	1822	2.157	1602	2.216	1792	2.952	1797	2.443	1753
α = .60	Pos	1.989	2478	2.746	2693	2.931	2492	4.149	2501	2.954	2541
	Neg	2.434	1814	2.196	1599	2.268	1800	3.073	1791	2.493	1751
α = .65	Pos	2.024	2487	2.769	2700	2.914	2485	4.145	2495	2.963	2542
	Neg	2.437	1805	2.246	1592	2.327	1807	3.169	1797	2.545	1750
α = .70	Pos	2.060	2504	2.788	2712	2.895	2482	4.153	2490	2.974	2547
	Neg	2.461	1788	2.314	1580	2.400	1810	3.276	1802	2.613	1745
α = .75	Pos	2.107	2510	2.828	2715	2.876	2482	4.160	2488	2.993	2549
	Neg	2.473	1782	2.382	1577	2.483	1810	3.384	1804	2.681	1743
α = .80	Pos	2.150	2523	2.850	2718	2.865	2481	4.160	2493	3.006	2554
	Neg	2.499	1769	2.456	1574	2.574	1811	3.499	1799	2.757	1738
α = .85	Pos	2.201	2532	2.876	2722	2.856	2484	4.162	2499	3.024	2559
	Neg	2.527	1716	2.536	1570	2.682	1808	3.613	1793	2.840	1733
α = .90	Pos	2.260	2537	2.902	2725	2.846	2491	4.169	2505	3.044	2565
	Neg	2.555	1755	2.618	1567	2.798	1801	3.723	1787	2.924	1727
α = .95	Pos	2.321	2539	2.928	2726	2.848	2490	4.190	2505	3.072	2565
	Neg	2.580	1753	2.704	1566	2.905	1802	3.815	1787	3.001	1727
α =1.00	Pos	1.884	3216	2.381	3385	2.278	3127	3.359	3143	2.476	3218
	Neg	4.243	1076	4.828	907	4.680	1165	6.069	1149	4.955	1074

MOE: MEAN ABSOLUTE ERROR (FILTERED DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	1.676	1.790	1.809	2.537	1.953
.10	1.652	1.772	1.767	2.512	1.926
.15	1.630	1.767	1.741	2.500	1.910
.20	1.612	1.769	1.731	2.501	1.903
.25	1.598	1.777	1.730	2.510	1.904
.30	1.589	1.789	1.737	2.526	1.910
.35	1.582	1.807	1.750	2.548	1.922
.40	1.577	1.830	1.768	2.572	1.937
.45	1.576	1.858	1.790	2.598	1.956
.50	1.585	1.890	1.816	2.624	1.979
.55	1.602	1.924	1.845	2.651	2.007
.60	1.621	1.958	1.876	2.678	2.033
.65	1.643	1.993	1.910	2.706	2.063
.70	1.667	2.028	1.949	2.734	2.095
.75	1.693	2.064	1.989	2.764	2.128

MOE: MEAN ABSOLUTE ERROR (FILTERED DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
α = .80	1.722	2.099	2.031	2.793	2.161
.85	1.755	2.134	2.075	2.824	2.197
.90	1.790	2.169	2.119	2.856	2.234
.95	1.826	2.203	2.164	2.888	2.270
1.00	1.863	2.238	2.211	2.921	2.308

MOE: MEAN FORECAST ERROR (FILTERED DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	-.360	.559	.336	1.024	.390
.10	-.343	.593	.338	1.009	.399
.15	-.325	.625	.336	.990	.407
.20	-.308	.655	.329	.968	.418
.25	-.290	.684	.317	.943	.414
.30	-.273	.710	.302	.916	.414
.35	-.256	.735	.283	.888	.413
.40	-.238	.758	.260	.861	.410
.45	-.221	.780	.234	.833	.407
.50	-.204	.800	.204	.807	.393
.55	-.186	.818	.173	.782	.397
.60	-.169	.834	.138	.760	.391
.65	-.151	.848	.102	.740	.385
.70	-.134	.861	.063	.724	.379
.75	-.117	.872	.023	.710	.372

MOE: MEAN FORECAST ERROR (FILTERED DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .80	-.099	.882	-.019	.701	.366
.85	-.082	.889	-.062	.695	.360
.90	-.064	.895	-.106	.694	.355
.95	-.047	.899	-.150	.697	.350
1.00	-.030	.901	-.195	.705	.345

MOE: ROOT MEAN SQUARE FORECAST ERROR (FILTERED DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
α = .05	7.161	9.275	6.519	12.782	8.934
.10	7.005	9.647	6.442	12.762	8.964
.15	6.873	10.016	6.425	12.801	9.029
.20	6.767	10.378	6.459	12.881	9.121
.25	6.686	10.727	6.538	12.991	9.236
.30	6.633	11.060	6.655	13.119	9.367
.35	6.609	11.375	6.810	13.258	9.513
.40	6.613	11.668	7.002	13.402	9.671
.45	6.645	11.940	7.229	13.545	9.840
.50	6.706	12.189	7.493	13.683	10.018
.55	6.793	12.414	7.791	13.813	10.203
.60	6.907	12.615	8.123	13.931	10.394
.65	7.045	12.793	8.487	14.037	10.591
.70	7.207	12.947	8.882	14.129	10.791
.75	7.392	13.080	9.302	14.208	10.996

MOE: ROOT MEAN SQUARE FORECAST ERROR (FILTERED DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .80	7.596	13.191	9.747	14.275	11.202
.85	7.819	13.282	10.211	14.331	11.411
.90	8.059	13.354	10.690	14.381	11.621
.95	8.316	13.410	11.180	14.428	11.847
1.00	8.587	13.452	11.677	14.479	12.049

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (FILTERED DATA) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .05	70.797	60.029	61.995	78.835	67.914
.10	69.799	59.134	60.786	77.937	66.914
.15	68.868	58.479	60.089	77.718	66.289
.20	68.024	58.112	59.852	78.118	66.027
.25	67.240	57.957	59.956	78.933	66.022
.30	66.644	57.954	60.288	80.088	66.244
.35	66.090	58.093	60.809	81.454	66.612
.40	65.589	58.373	61.432	82.898	67.073
.45	65.330	58.797	62.140	84.355	67.656
.50	65.091	59.336	62.957	85.775	68.290
.55	65.026	60.017	63.837	87.151	69.008
.60	65.028	60.747	64.760	88.471	69.752
.65	65.093	61.647	65.725	89.709	70.519
.70	65.216	62.394	66.759	90.823	71.298
.75	65.415	63.285	67.821	91.833	72.089

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (FILTERED DATA) (CONTINUED) MODEL: ES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
α = .80	65.643	64.197	68.918	92.724	72.871
.85	65.939	65.188	70.014	93.519	73.665
.90	66.272	66.259	71.090	94.235	74.464
.95	66.612	67.356	72.133	94.862	75.241
1.00	67.028	68.500	73.167	95.390	76.021

MOE: MEAN ERROR (FILTERED DATA) MODEL: EXPONENTIAL SMOOTHING

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\bar{X}$	AVE. NO.
α = .05	Pos	1.271	1539	2.095	1668	2.028	1573	3.327	1592	2.180	1593
	Neg	2.110	1435	1.401	1306	1.564	1401	1.629	1382	1.676	1381
α = .10	Pos	1.268	1536	2.105	1671	1.993	1571	3.294	1590	2.165	1592
	Neg	2.063	1438	1.346	1303	1.515	1403	1.615	1384	1.635	1382
α = .15	Pos	1.266	1533	2.125	1674	1.958	1578	3.242	1601	2.148	1597
	Neg	2.018	1441	1.306	1300	1.497	1396	1.636	1373	1.614	1377
α = .20	Pos	1.263	1536	2.158	1671	1.947	1573	3.244	1590	2.153	1593
	Neg	1.985	1438	1.272	1303	1.488	1401	1.648	1384	1.598	1381
α = .25	Pos	1.249	1557	2.157	1696	1.935	1574	3.219	1595	2.140	1606
	Neg	1.982	1417	1.272	1278	1.501	1400	1.690	1379	1.611	1368
α = .30	Pos	1.273	1538	2.193	1695	1.931	1570	3.238	1581	2.159	1596
	Neg	1.929	1436	1.254	1279	1.520	1404	1.719	1393	1.606	1378
α = .35	Pos	1.283	1538	2.228	1697	1.934	1563	3.282	1557	2.182	1589
	Neg	1.903	1436	1.249	1277	1.547	1411	1.742	1417	1.610	1385
α = .40	Pos	1.274	1563	2.250	1711	1.937	1557	3.294	1550	2.189	1595
	Neg	1.913	1411	1.262	1263	1.583	1417	1.788	1424	1.637	1379
α = .45	Pos	1.309	1539	2.291	1712	1.942	1550	3.311	1541	2.213	1586
	Neg	1.862	1435	1.271	1262	1.626	1424	1.832	1433	1.648	1388
α = .50	Pos	1.315	1562	2.315	1728	1.940	1549	3.309	1542	2.220	1595
	Neg	1.884	1412	1.302	1246	1.682	1425	1.888	1432	1.689	1379

MOE: MEAN ERROR (FILTERED DATA) MODEL: ES

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\overline{X}$	AVE. NO.
α = .55	Pos	1.357	1552	2.376	1716	1.948	1540	3.314	1541	2.249	1587
	Neg	1.870	1422	1.308	1250	1.734	1434	1.940	1433	1.713	1387
α = .60	Pos	1.386	1559	2.417	1718	1.954	1533	3.307	1546	2.266	1589
	Neg	1.881	1415	1.331	1256	1.794	1441	1.998	1428	1.751	1385
α = .70	Pos	1.445	1578	2.488	1727	1.966	1522	3.350	1535	2.312	1591
	Neg	1.919	1396	1.392	1247	1.931	1452	2.078	1439	1.830	1383
α = .75	Pos	1.484	1580	2.427	1728	1.964	1523	3.368	1534	2.336	1591
	Neg	1.931	1394	1.422	1246	2.015	1451	2.121	1440	1.872	1383
α = .80	Pos	1.522	1586	2.556	1734	1.968	1521	3.383	1536	2.357	1594
	Neg	1.951	1388	1.460	1240	2.099	1453	2.164	1438	1.919	1380
α = .85	Pos	1.567	1588	2.591	1735	1.969	1521	3.403	1538	2.383	1596
	Neg	1.971	1386	1.494	1239	2.188	1453	2.305	1436	1.965	1378
α = .90	Pos	1.616	1589	2.623	1737	1.966	1523	3.424	1542	2.407	1598
	Neg	1.992	1385	1.532	1237	2.281	1451	2.245	1432	2.013	1376
α = .95	Pos	1.664	1590	2.655	1738	1.968	1522	3.456	1543	2.436	1598
	Neg	2.012	1384	1.570	1236	2.370	1452	2.277	1431	2.057	1376
α =1.00	Pos	1.268	2150	2.040	2288	1.453	2063	2.553	2112	1.829	2153
	Neg	3.415	824	2.897	684	3.928	911	3.824	862	3.516	821

MOE: MEAN ABSOLUTE ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING AVERAGE

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN ABSOLUTE ERROR (RAW DATA)					
2 QTR	2.228	2.599	2.667	3.756	2.813
3 QTR	2.267	2.514	2.692	3.592	2.766
4 QTR	2.230	2.431	2.729	3.558	2.737
MOE: MEAN ABSOLUTE ERROR (FILTERED DATA)					
2 QTR	1.652	2.018	1.886	2.702	2.065
3 QTR	1.697	1.922	1.798	2.617	2.009
4 QTR	1.599	1.773	1.745	2.529	1.912

MOE: MEAN FORECAST ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING AVERAGE

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN FORECAST ERROR (RAW DATA)					
2 QTR	.122	1.031	.818	1.030	.750
3 QTR	-.139	.939	1.077	1.380	.814
4 QTR	-.081	.753	1.093	1.643	.852
MOE: MEAN FORECAST ERROR (FILTERED DATA)					
2 QTR	-.263	.887	.255	.607	.372
3 QTR	-.412	.726	.396	.875	.396
4 QTR	-.291	.592	.349	1.002	.413

MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA AND FILTERED DATA)

MODEL: MOVING AVERAGE

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA)					
2 QTR	10.424	17.436	13.756	18.862	15.120
3 QTR	10.618	16.594	14.079	17.473	14.691
4 QTR	10.770	15.809	14.855	17.306	14.685
MOE: ROOT MEAN SQUARE FORECAST ERROR (FILTERED DATA)					
2 QTR	7.142	13.779	8.071	15.102	11.024
3 QTR	7.721	12.032	6.521	13.821	10.024
4 QTR	6.687	9.963	6.298	12.697	8.911

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING AVERAGE

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA)					
2 QTR	66.289	60.152	62.868	90.820	70.032
3 QTR	68.584	60.117	59.012	83.442	67.789
4 QTR	67.418	62.106	59.412	76.833	66.442
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (FILTERED DATA)					
2 QTR	68.054	61.057	65.401	93.942	72.114
3 QTR	69.094	60.068	61.688	85.694	69.136
4 QTR	67.252	58.786	60.943	78.398	66.345

MOE: MEAN ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING AVERAGE

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\overline{X}$	AVE. NO.
MOE: MEAN ERROR (RAW DATA)											
2 QTRS	Pos	1.817	2775	2.498	3119	2.527	2959	3.168	2839	2.615	2923
	Neg	2.980	1517	2.869	1173	2.977	1333	4.026	1453	3.213	1369
3 QTRS	Pos	1.794	2545	2.554	2901	2.860	2828	3.869	2758	2.769	2758
	Neg	2.956	1747	2.432	1391	2.368	1464	3.095	1534	2.713	1534
4 QTRS	Pos	1.885	2446	2.476	2759	3.029	2708	4.079	2736	2.867	2662
	Neg	2.686	1846	2.348	1533	2.217	1584	2.642	1556	2.473	1630
MOE: MEAN ERROR (FILTERED DATA											
2 QTRS	Pos	1.151	1795	2.081	2075	1.654	1925	2.670	1843	1.889	1910
	Neg	2.415	1179	1.871	899	2.311	1049	2.754	1131	2.338	1064
3 QTRS	Pos	1.174	1627	2.083	1891	1.793	1820	2.931	1772	1.995	1778
	Neg	2.329	1347	1.642	1083	1.807	1154	2.156	1202	1.984	1196
4 QTRS	Pos	1.249	1557	1.981	1775	1.817	1714	2.995	1753	2.011	1700
	Neg	1.983	1417	1.465	1199	1.647	1260	1.860	1221	1.739	1274

MOE: MEAN ABSOLUTE ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING LEAST SQUARES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN ABSOLUTE ERROR (RAW DATA)					
2 QTR	4.182	4.760	5.074	6.099	5.029
3 QTR	3.396	3.745	3.716	5.262	4.030
4 QTR	3.009	3.522	3.227	4.609	3.592
MOE: MEAN ABSOLUTE ERROR (FILTERED DATA)					
2 QTR	3.427	3.591	3.935	4.458	3.853
3 QTR	2.498	2.920	2.898	3.586	2.976
4 QTR	2.264	2.747	2.482	3.274	2.692

MOE: MEAN FORECAST ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING LEAST SQUARES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN FORECAST ERROR (RAW DATA)					
2 QTR	.801	.509	-.468	.446	.322
3 QTR	.870	1.043	-.129	.134	.480
4 QTR	.248	1.362	.441	.233	.571
MOE: MEAN FORECAST ERROR (FILTERED DATA)					
2 QTR	.437	.931	-1.097	.900	.293
3 QTR	.269	1.222	-.476	.169	.296
4 QTR	-.315	1.242	.053	.269	.312

MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA AND FILTERED DATA)

MODEL: MOVING LEAST SQUARES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA)					
2 QTR	19.298	22.338	27.728	27.722	24.272
3 QTR	17.628	20.498	20.461	25.201	20.947
4 QTR	14.306	21.431	15.076	23.165	18.495
MOE: ROOT MEAN SQUARE FORECAST ERROR (FILTERED DATA)					
2 QTR	15.668	16.546	23.457	19.424	18.774
3 QTR	12.241	17.487	17.564	17.813	16.276
4 QTR	10.127	18.810	11.243	18.063	14.561

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING LEAST SQUARES

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA)					
2 QTR	134.285	129.736	138.893	169.587	143.125
3 QTR	100.589	98.215	100.274	143.005	110.533
4 QTR	89.346	86.960	87.141	124.309	96.939
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (FILTERED DATA)					
2 QTR	140.254	131.195	143.003	162.691	144.286
3 QTR	102.983	97.999	104.272	139.711	111.241
4 QTR	87.162	85.239	89.207	126.127	96.959

MOE: MEAN ERROR (RAW DATA AND FILTERED DATA) MODEL: MOVING LEAST SQUARES

MODEL		QTR 5		QTR 6		QTR 7		QTR 8			
		ERROR	OBS	ERROR	OBS	ERROR	OBS	ERROR	OBS	$\overline{X}$	AVE. NO.
MOE: MEAN ERROR (RAW DATA)											
2 QTRS	Pos	3.291	3249	3.436	3291	3.310	2986	6.099	3133	4.034	3165
	Neg	6.957	1043	9.116	1001	9.106	1306	4.484	1159	7.416	1127
3 QTRS	Pos	3.102	2952	3.243	3169	2.691	2861	4.066	2848	3.276	2958
	Neg	4.0446	1340	5.165	1123	5.765	1431	7.621	1444	5.649	1334
4 QTRS	Pos	2.434	2872	3.281	3195	2.640	2982	3.648	2849	3.001	2975
	Neg	4.171	1420	4.225	1097	4.564	1310	6.509	1443	4.867	1317
MOE: MEAN ERROR (FILTERED DATA)											
2 QTRS	Pos	2.666	2155	3.061	2197	2.180	1936	3.797	2098	2.926	2097
	Neg	5.429	819	5.090	777	7.209	1038	6.039	876	5.942	877
3 QTRS	Pos	2.161	1905	2.936	2098	1.963	1835	3.040	1837	2.525	1919
	Neg	3.101	1069	2.883	876	4.405	1139	4.470	1137	3.715	1055
4 QTRS	Pos	1.562	1856	2.822	2102	1.938	1946	2.839	1856	2.209	1940
	Neg	3.431	1118	2.566	872	3.515	1028	3.998	1118	3.378	1034

MOE: MEAN ABSOLUTE ERROR (RAW DATA AND FILTERED DATA)

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
MOE: MEAN ABSOLUTE ERROR (RAW DATA)					
SPCC	2.197	2.497	2.760	3.614	2.767
ARR	2.707	2.831	2.789	3.970	3.074
DEMAND	7.659	6.703	7.550	8.703	7.654
LAG	8.957	5.736	5.198	4.877	6.192
REG-ADVICE	3.394	3.935	4.324	5.185	4.210
MOE: MEAN ABSOLUTE ERROR (FILTERED DATA)					
SPCC	1.584	1.758	1.727	2.521	1.898
ARR	2.065	2.120	2.022	2.760	2.262
DEMAND	6.470	5.124	5.681	7.105	6.095
LAG	2.036	1.827	1.996	2.536	2.099
REG-ADVICE	2.731	3.303	3.116	3.914	3.266

MOE: MEAN FORECAST ERROR (RAW DATA AND FILTERED DATA)

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\bar{X}$
MOE: MEAN FORECAST ERROR (RAW DATA)					
SPCC	-.007	.944	1.092	1.577	.902
ARR	-.523	.305	.314	.744	.210
DEMAND	1.768	1.169	1.172	1.508	1.404
LAG	-6.389	-2.289	-.855	.460	-2.268
REG-ADVICE	1.726	2.777	1.965	1.178	1.912
MOE: MEAN FORECAST ERROR (FILTERED DATA)					
SPCC	-.245	.748	.404	1.006	.478
ARR	-.788	.333	-.010	.641	.044
DEMAND	2.845	1.367	.212	.633	1.264
LAG	-1.216	-.270	-.549	-.191	-.557
REG-ADVICE	.880	2.039	.521	-.736	.676

MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA AND FILTERED DATA)

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: ROOT MEAN SQUARE FORECAST ERROR (RAW DATA)					
SPCC	10.623	16.817	15.707	18.368	15.379
ARR	12.001	16.346	13.189	18.507	15.011
DEMAND	92.850	54.772	67.198	68.481	70.825
LAG	300.746	125.601	75.924	41.812	136.021
REG-ADVICE	22.359	31.496	27.169	26.982	27.002
MOE: ROOT MEAN SQUARE FORECAST ERROR (FILTERED DATA)					
SPCC	6.710	10.847	6.463	13.177	9.299
ARR	9.281	11.347	7.184	13.405	10.304
DEMAND	97.970	46.959	65.202	69.936	70.017
LAG	8.464	6.895	7.610	12.897	8.967
REG-ADVICE	18.640	29.881	21.096	16.860	21.619

MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA AND FILTERED DATA)

MODEL	QTR 5	QTR 6	QTR 7	QTR 8	$\overline{X}$
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (RAW DATA)					
SPCC	65.745	58.459	57.398	74.215	63.954
ARR	87.441	78.692	77.084	100.312	85.882
DEMAND	165.868	152.139	154.213	191.059	165.820
LAG	233.992	202.084	138.421	122.325	174.206
REG-ADVICE	84.574	68.805	91.554	116.058	90.248
MOE: MEAN ABSOLUTE PERCENTAGE ERROR (FILTERED DATA)					
SPCC	66.252	55.640	57.083	77.296	64.068
ARR	85.979	76.218	78.155	95.412	83.941
DEMAND	111.112	102.911	104.051	210.699	132.193
LAG	104.670	82.023	87.752	111.379	96.456
REG-ADVICE	90.966	72.276	96.960	133.155	98.339

MOE: MEAN ERROR (RAW DATA)

MODEL		QTR 5 ERROR	QTR 5 OBS	QTR 6 ERROR	QTR 6 OBS	QTR 7 ERROR	QTR 7 OBS	QTR 8 ERROR	QTR 8 OBS	$\overline{X}$	AVE. NO.
SPCC	Pos	1.840	2554	2.626	2812	3.008	2748	4.081	2730	2.889	2711
	Neg	2.722	1738	2.253	1480	2.319	1544	2.800	1562	2.524	1581
ARR	Pos	1.862	2518	2.521	2670	2.647	2516	4.102	2466	2.783	2543
	Neg	3.907	1774	3.343	1622	2.991	1776	3.792	1826	3.508	1749
DEMAND	Pos	8.804	2298	6.784	2490	7.502	2495	8.655	2532	7.936	2454
	Neg	6.339	1994	6.590	1802	7.617	1797	8.774	1760	7.330	1836
LAG	Pos	3.030	1819	3.636	2035	4.722	1974	5.860	1955	4.312	1946
	Neg	13.317	2473	7.631	2257	5.604	2318	4.056	2337	7.652	2346
REG-	Pos	3.969	2769	4.790	3007	5.188	2602	5.841	2338	4.947	2679
ADVICE	Neg	2.351	1523	1.935	1285	2.997	1690	4.401	1954	2.921	1613

MOE: MEAN ERROR (FILTERED DATA)

MODEL		QTR 5		QTR 6		QTR 7		QTR 8			
		ERROR	OBS	ERROR	OBS	ERROR	OBS	ERROR	OBS	$\bar{X}$	AVE. NO.
SPCC	Pos	1.209	1647	2.044	1823	1.795	1766	2.988	1756	2.009	1748
	Neg	2.050	1327	1.305	1151	1.629	1208	1.850	1218	1.709	1226
ARR	Pos	1.198	1585	2.151	1696	1.923	1556	3.319	1524	2.148	1590
	Neg	3.054	1389	2.081	1278	2.131	1418	2.174	1450	2.360	1384
DEMAND	Pos	10.487	1321	6.504	1484	5.966	1469	7.631	1508	7.647	1446
	Neg	3.261	1653	3.750	1490	5.403	1505	6.566	1466	4.745	1528
LAG	Pos	1.335	914	2.148	1078	2.138	1007	3.467	1006	2.272	1001
	Neg	2.348	2060	1.644	1896	1.925	1967	2.061	1968	1.995	1973
REG-ADVICE	Pos	3.131	1715	4.161	1909	3.474	1557	3.565	1326	3.583	1627
	Neg	2.187	1259	1.765	1065	2.724	1417	4.196	1648	2.718	1347

APPENDIX E

ACRONYM LISTING

ACR	actual carcass return
ADV	advice code
APA	Appropriations Procurement Account
ARD	actual recurring demand
ARR	adaptive response rate
COG	cognizant symbol
CPS	collection point surveys
CRF	carcass return forecast
DDF	Due-in/Due-out File
DEMAND	demand/return model
DEN	data element number
DLR	depot level repairable
DOP	designated overhaul point
DOPS	designated overhaul point survey
EOQ	economic order quantity
ERQ	economic repair quantity
ES	exponential smoothing
FMSO	Navy Fleet Material Support Office
ICP	inventory control point
IHF	Inventory History File
IND	inductions into the repair phase
MA	moving average model

MAD	mean absolute deviation
MAE	mean absolute error
MAFE	mean absolute forecast error
MAPE	mean absolute percentage error
MDF	Master Data File
MFE	mean forecast error
MLS	moving least squares model
MNE	mean negative error
MOE	measures of effectiveness
MPD	movement priority designation
MPE	mean positive error
NAVAIR	Naval Air Systems Command
NAVELEX	Naval Electronics Systems Command
NAVSEA	Naval Sea Systems Command
NAVSUP	Naval Supply Systems Command
NIIN	national item identification number
NPS	Naval Postgraduate School
NRFI	not ready for issue
NSF	Navy Stock Fund
NSN	national stock number
PPR	Planned Program Requirements File
QTR	quarter
RD	recurring demand
RDF	recurring demand forecast
REG	regression model
RFI	ready for issue

RMSFE	root mean square forecast error
ROH	regular overhaul
RP	reorder point
RSR	repair survival rate
SAS	Statistical Analysis System
SDR	Supply Demand Review
SMA	supply material availability
SPCC	Navy Ships Parts Control Center
STRAT	Stratification
THF	Transaction History File
TIR	transaction item reporting
UICP	Uniform Automated Data Processing System - Inventory Control Point
WR	wearout rate

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